Inattention and Inertia in Household Finance: Evidence from the Danish Mortgage Market

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First draft: July 2014
This version: May 2015

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We thank the Sloan Foundation for financial support. We are grateful to the Association of Danish Mortgage Banks (ADMB) for providing data and facilitating dialogue with the individual mortgage banks, and to senior economists Bettina Sand and Kaare Christensen at the ADMB for providing us with valuable institutional details. We thank Joao Cocco, Xavier Gabaix, Tomasz Piskorski, Tano Santos, Antoinette Schoar, and seminar participants at the Board of Governors of the Federal Reserve/GFLEC Financial Literacy Seminar at George Washington University, the NBER Summer Institute Household Finance Meeting, the Riksbank-EABCN conference on Inequality and Macroeconomics, the American Economic Association 2015 Meeting, the Real Estate Seminar at UC Berkeley, the Federal Reserve Bank of New York, Copenhagen Business School, and Columbia Business School for many useful comments, and Josh Abel for excellent and dedicated research assistance.

Abstract

This paper studies the refinancing behavior of Danish households during a recent period of declining interest rates. Danish data are particularly suitable for this purpose because the Danish mortgage system imposes few barriers to refinancing, and demographic and economic characteristics of mortgage borrowers can be accurately measured. The paper estimates a mixture model of household refinancing types in which household characteristics affect both inattention (a low proportion of rational refinancers) and inertia (a low probability that inattentive households refinance). Many characteristics move inattention and inertia in the same direction, implying a positive cross-sectional correlation of 0.67 between these two household attributes. Younger, better educated, and higher-income households have less inertia and less inattention. Financial wealth and housing wealth have opposite effects, with the least inertia and inattention among households whose housing wealth is high relative to their financial wealth.

1 Introduction

Inertia, or sluggish adaptation to altered circumstances, is endemic in household financial decision making. It has been documented for participation, saving, and asset allocation decisions in retirement savings plans (Agnew, Balduzzi, and Sunden 2003, Choi, Laibson, Madrian, and Metrick 2002, 2004, Madrian and Shea 2001) and for portfolio rebalancing in response to fluctuations in risky asset prices (Bilias, Georgarakos, and Haliassos 2010, Brunnermeier and Nagel 2008, Calvet, Campbell, and Sodini 2009a).

Mortgage refinancing is a particularly important household decision, given the size of mortgages relative to other household assets and liabilities. Inertia and the related phenomenon of inattention, the inability to accurately perceive incentives, appear to reduce refinancing rates substantially. In the US fixed-rate mortgage (FRM) system, refinancing inertia is essential for understanding empirical prepayment behavior, the main preoccupation of a large literature on the pricing and hedging of mortgage-backed securities in the years before the global financial crisis of the late 2000s (Schwartz and Torous 1989, McConnell and Singh 1994, Stanton 1995, Bennett, Peach, and Peristiani 2001). Random time-variation in the degree of inertia accounts for prepayment risk, which in turn affects the pricing of mortgage-backed securities (Deng, Quigley, and Van Order 2000, Gabaix, Krishnamurthy, and Vigneron 2007). In the UK adjustable-rate mortgage (ARM) system, teaser rates also generate incentives to refinance, and here too many people fail to refinance when it would be optimal to do so (Miles 2004).

This evidence raises several interesting questions. First, are there measurable differences between people who refinance appropriately and those who fail to do so? Evidence from the US suggests that this is the case (LaCour-Little 1999, Campbell 2006, Schwartz 2006, Agarwal, Rosen, and Yao 2012). However, it is challenging to measure borrower characteristics in the US system since these are reported only at the time of a mortgage application through the form required by the Home Mortgage Disclosure Act (HMDA), and hence one cannot directly compare the characteristics of refinancers and non-refinancers at a point in time. An alternative is to use survey data, but these are extremely noisy (Schwartz 2006).

Second, how common and how costly are errors of commission, where households refinance their mortgages too soon, relative to errors of omission, where households refinance their mortgages too late or fail to refinance them at all? Agarwal, Driscoll, and Laibson (2013) point out that because interest rates are random and refinancing involves fixed monetary and time costs, the optimal refinancing decision is the solution to a real options problem. It is not optimal to refinance as soon as the interest savings cover the fixed costs of refinancing, because waiting may lead to a greater interest saving if interest rates decline further. They present an approximate closed-form solution to the refinancing problem, which Agarwal, Rosen, and Yao (2012) use to measure omission and commission error rates. However Agarwal, Rosen, and Yao can only study delays in refinancing among refinancers, since they do not have data on people who fail to refinance altogether. Keys, Pope, and Pope (2014) use data on outstanding mortgages to circumvent this problem, but give up the ability to measure borrower characteristics contemporaneously.

Third, to what extent are failures to refinance driven by constraints such as poor credit ratings or negative home equity, versus failures to understand refinancing incentives? This is a pervasive issue in empirical research using US data (Archer, Ling, and McGill 1996, Caplin, Freeman, and Tracy 1997, Campbell 2006, Schwartz 2006, Keys, Pope, and Pope 2014). In the aftermath of the global financial crisis, the US government has tried to relax refinancing constraints through the Home Affordable Refinance Program (HARP), but the effectiveness of this program remains an outstanding research question (Zandi and deRitis 2011, Tracy and Wright 2012, Zhu 2012).

In this paper we study refinancing decisions using data from Denmark. The Danish mortgage system is similar to the US system in that it is dominated by FRMs, but different in that households are free to refinance whenever they choose to do so, even if their home equity is negative or their credit standing has deteriorated, provided that they do not increase their outstanding principal balance. This allows us to study refinancing inertia without having to control for constraints. In addition, the Danish statistical system provides us with accurate administrative data on household demographic and financial characteristics, for all mortgage borrowers including both refinancers and non-refinancers.

We use these high-quality Danish data to study how household characteristics affect the responsiveness of households to refinancing incentives, as well as the unconditional or baseline refinancing probability. In order to separately measure inertia and inattention, we estimate a mixture model in which households are of two types, "levelheads" who respond rationally to refinancing incentives and "woodheads" who refinance at a fixed rate regardless of incentives. Both the proportion of levelheads in the population and the refinancing probability of woodheads may vary with demographic characteristics. We interpret a low proportion of levelheads within a demographic group as a measure of the group's inattention, and a low woodhead refinancing probability as a pure measure of the group's inertia after controlling for the level of inattention. We find that inertia and inattention have a strong positive, although not perfect, cross-sectional correlation.

Our work fits into a broader literature on the difficulties households have in managing their mortgage borrowing. Campbell and Cocco (2003, 2015) specify models of optimal choice between FRMs and ARMs, and optimal prepayment and default decisions, showing how challenging it is to make these decisions correctly. Chen, Michaux, and Roussanov (2013) similarly study decisions to extract home equity through cash-out refinancing, while Bhutta and Keys (2013) and Khandani, Lo, and Merton (2013) argue that households used cash-out refinancing to borrow too aggressively during the housing boom of the early 2000s. Bucks and Pence (2008) provide direct survey evidence that ARM borrowers are unaware of the exact terms of their mortgages, specifically the range of possible variation in their mortgage rates. Woodward and Hall (2010, 2012) study the fees that borrowers pay at mortgage origination, arguing that insufficient shopping effort leads to excessive fees.

The organization of the paper is as follows. Section 2 explains the Danish mortgage system and household data. Section 3 presents our mixture model of household refinancing types. Section 4 estimates the model empirically, and section 5 concludes. An online appendix (Andersen, Campbell, Nielsen, and Ramadorai 2015) provides supporting details.

2 The Danish Mortgage System and Household Data

2.1 The Danish mortgage system

The Danish mortgage system has attracted considerable attention internationally because, while similar to the US system in offering long-term fixed-rate mortgages without prepayment penalties, it has numerous design features that differ from the US model and have performed well in recent years (Campbell 2013, Gyntelberg et al. 2012, Lea 2011). In this section we briefly review the funding of Danish mortgages and the rules governing refinancing. (The online appendix provides a few additional details on the Danish system.)

A. Mortgage funding

Danish mortgages, like those in some other continental European countries, are funded using covered bonds: obligations of mortgage lenders that are collateralized by pools of mortgages. The Danish market for covered mortgage bonds is the largest in the world, both in absolute terms and relative to the size of the economy. The market value of all Danish outstanding mortgage bonds in 2012 was DKK 2,456bn (EUR 330bn), exceeding the Danish GDP of DKK 1,826bn (EUR 245bn).[2]

Mortgages in Denmark are issued by mortgage banks that act as intermediaries between investors and borrowers. Investors buy mortgage bonds issued by the mortgage bank, and borrowers take out mortgages from the bank. All lending is secured and mortgage banks have no influence (apart from the initial screening) on the yield on the loans granted, which is entirely determined by the market. There is no direct link between the borrower and the investor. Instead investors buy bonds that are backed by a pool of borrowers. If a borrower defaults, the mortgage bank must replace the defaulted mortgage in the pool that backs the mortgage bond. This ensures that investors are unaffected by defaults in their borrower pool so long as the mortgage bank remains solvent.

In the event of a borrower default, the mortgage bank can enforce its contractual right by triggering a forced sale (foreclosure) which is carried through by the enforcement court,

[2] Data from the European Covered Bonds Council show that the largest covered mortgage bond markets in 2013 were, in order, Denmark, Spain, Sweden, France, and Germany. Germany had the largest overall covered bond market, followed by Denmark and Spain.

part of the court system in Denmark. To the extent that the proceeds of a forced sale are insufficient to pay off mortgages, uncovered claims are converted to personal claims held by the mortgage bank against the borrower. In other words Danish mortgages (like those elsewhere in Europe) have personal recourse against borrowers.

The Danish mortgage system originated in 1795 when a huge fire burned one in four houses in Copenhagen to the ground. To finance the reconstruction, lenders formed a mortgage association in 1797 and the first Danish mortgages were issued on real property on the basis of joint and several liability to enhance credit quality. Over the past 200-plus years the market has experienced no mortgage bond defaults, and only in a very few cases have payments to investors been delayed. The last example of delayed payments to mortgage bond investors occurred in the 1930s.

This track record is partly attributable to the legal framework, which was first introduced in 1850, with successive changes resulting in the current framework, which dates from 2007. The legal framework is designed to protect mortgage bond investors and confines the activities of mortgage banks to mortgage lending funded only through the issuance of mortgage bonds. Mortgage loans serving as collateral must meet restrictive eligibility criteria including LTV limits and valuation of property requirements laid down in the legislation. For instance, for private residential properties the LTV limit is 80% and mortgage banks are obliged to assess the market value of pledged properties at the time of granting the loans. The maximum loan maturity is 30 years, with an option for interest-only periods of a maximum of 10 years for private residential properties. Mortgage banks may not grant loans exceeding these limits, even to borrowers who are extremely creditworthy. However, refinancing is relatively unconstrained even for loans exceeding the LTV limit, as we discuss more fully below and in the internet appendix.

Danish mortgage bonds are currently issued by seven mortgage banks. While mortgages on various types of real properties are eligible as collateral for mortgage bonds, mortgages on residential properties dominate most collateral pools. Owner-occupied housing makes up around 60% of mortgage pools, followed by around 20% for rental and subsidized housing. Agriculture and commercial properties make up the remaining 20% of the market.

B. Refinancing

Mortgage borrowers in Denmark have the right to prepay their mortgages without penalty. This is similar to the US system but differs from another leading fixed-rate European mortgage system, the German system, where a fixed-rate mortgage can only be prepaid at a penalty that compensates the mortgage lender for any decline in interest rates since the mortgage was originated. However the prepayment system in Denmark also differs from the US system in several important respects.

The Danish mortgage system imposes minimal barriers to any refinancing that does not "cash out" (in a sense to be made more precise below). Danish borrowers can refinance their mortgages to reduce their interest rate and/or extend their loan maturity, without cashing out, even if their homes have declined in value so they have negative home equity. Related to this, refinancing without cashing out does not require a review of the borrower's credit quality. Denmark does not have a system of continuous credit scores like the widely used FICO scores in the US. Instead, there is what amounts to a zero/one scoring system that can be used to label an individual as a delinquent borrower (dårlig betaler) who has unpaid debt outstanding. A delinquent borrower would be unlikely to obtain a mortgage, but a borrower with an existing mortgage can refinance, without cashing out, even if he or she has been labeled as delinquent since the mortgage was taken out. These features of the system imply that all mortgage borrowers can benefit from a decline in interest rates, even in a weak economy with declining house prices and consumer deleveraging.

The mechanics of refinancing in Denmark are as follows. The mortgage borrower must repurchase mortgage bonds corresponding to the mortgage debt, and deliver them to the mortgage lender. This repurchase can be done either at market value or at face value. The option to refinance at market value becomes relevant if interest rates rise; it prevents "lock-in" by allowing homeowners who move to buy out their old mortgages at a discounted market value rather than prepaying at face value as would be required in the US system. It also allows homeowners to take advantage of disruptions in the mortgage bond market by effectively buying back their own debt if a mortgage-bond fire sale occurs. In an environment of declining interest rates such as the one we study, the option to refinance at face value is relevant.

An important point is that mortgage bonds in Denmark are issued with discrete coupon rates, historically at integer levels such as 4% or 5%.[3] Market yields, of course, fluctuate continuously. To eliminate the possibility of instantaneous advantageous refinancing, Danish mortgage bonds are issued at a discount to face value, in other words with a coupon somewhat below the current market yield. This implies that to raise, say, DKK 1 million for a mortgage, bonds must be issued with a face value which is higher than DKK 1 million. Refinancing the mortgage requires buying the full face value of the bonds that were originally issued to finance it. Therefore the interest saving from refinancing in the Danish system is given by the spread between the coupon rate on the old mortgage bond (not the yield on the mortgage when it was issued) and the yield on a new mortgage.

An example may make this easier to understand. Suppose that a household requires a loan of DKK 1 million (about $190,000 or EUR 130,000) in order to purchase a house. Suppose that the market yield on a mortgage bond of the required term is 4.25%, but the coupon rate on the bond is somewhat lower at 4%. As a result of this difference between the coupon rate and the market yield, the DKK 1 million loan must be financed by issuing bonds in the market with a face value which is higher than DKK 1 million (say DKK 1.1

[3]More recently, bonds have been issued with non-integer coupons (2.5% and 3.5%) in response to the current low-interest-rate environment.

million). The principal balance of the mortgage is initially DKK 1.1 million.

Now consider what happens if market yields drop to 3.25%. The borrower can refinance by purchasing the original mortgage bond at face value and delivering it to the mortgage bank. To fund the purchase, the borrower will issue new mortgage bonds carrying the current market yield of 3.25%, and a lower discrete coupon (3% in this example). The interest saving from refinancing is $4\% - 3.25\% = 0.75\%$. This is the spread between the original coupon rate at issuance and the current market yield, rather than the spread between the old and new yields.

Since this transaction requires issuing a new mortgage bond with a market value of DKK 1.1 million and a face value above DKK 1.1 million, the principal balance of the mortgage increases as a result of the refinancing. However, it does not count as a cash-out refinancing provided that the market value of the newly issued mortgage bond is no greater than the face value of the old mortgage bond.

Cash-out refinancing does require sufficiently positive home equity and good credit status. For this reason, cash-out refinancing has been less common in Denmark in the period we examine since the onset of the housing downturn in the late 2000s. In our dataset 27% of refinancings are associated with an increase in mortgage principal of 10% or more, enough to classify these as cash-out refinancings with a high degree of confidence. In the paper we present results that include these refinancings, but in the online appendix we report broadly similar results excluding them.

2.2 Danish household data

A. Data sources

We assemble a unique dataset from Denmark. Our dataset covers the universe of adult Danes in the period between 2008 and 2012, and contains demographic and economic information. We derive data from five different administrative registers made available through Statistics Denmark.

We obtain mortgage data from the Association of Danish Mortgage Banks (Realkreditrådet) and the Danish Mortgage Banks' Federation (Realkreditforeningen). The data cover the 5 largest mortgage banks with an aggregated market share of 94.2% of the market value of all mortgages in Denmark. The residual mortgages are issued by two smaller mortgage banks. The data contain the personal identification number of borrowers, as well as a mortgage id, and information on the terms of the mortgage (principal, outstanding principal, coupon, annual fees, maturity, loan-to-value, issue date, etc.) The mortgage data are available annually from 2009 to 2011.

We obtain demographic information from the official Danish Civil Registration System (CPR Registeret). These records include the individual's personal identification number (CPR), as well as their name; gender; date of birth; and the individual's marital history (number of marriages, divorces, and history of spousal bereavement). The administrative record also contains a unique household identification number, as well as CPR numbers of each individual's spouse and any children in the household. We use these data to obtain demographic information about the borrower. The sample contains the entire Danish population and provides a unique identifying number across individuals, households, and time.

We obtain income and wealth information from the official records at the Danish Tax Authority (SKAT). This dataset contains total and disaggregated income and wealth information by CPR numbers for the entire Danish population. SKAT receives this information directly from the relevant third-party sources, because employers supply statements of wages paid to their employees, and financial institutions supply information to SKAT on their customers' deposits, interest paid (or received), security investments, and dividends. Because taxation in Denmark mainly occurs at the source level, the income and wealth information are highly reliable.

Some components of wealth are not recorded by SKAT. The Danish Tax Authority does not have information about individuals' holdings of unbanked cash, the value of their cars, their private debt (i.e., debt to private individuals), pension savings, private businesses, or other informal wealth holdings. This leads some individuals to be recorded as having negative net financial wealth because we observe debts but not corresponding assets, for example in the case where a person has borrowed to finance a new car.

We obtain the level of education from the Danish Ministry of Education (Undervisningsministeriet). This register identifies the highest level of education and the resulting professional qualifications. On this basis we calculate the number of years of schooling.

Finally, we use data on medical treatments and hospitalizations from the Danish National Board of Health (Sundhedsstyelsen) to calculate the total number of days in hospital during the year. This dataset records medical treatments and discharges from hospitals.

B. Sample selection

Our sample selection entails linking individual mortgages to the household characteristics of borrowers. We define a household as one or two adults living at the same postal address. To be able to credibly track the ownership of each mortgage we additionally require that each household has an unchanging number of adult members over two subsequent years. This allows us to identify 2,727,782 households in 2011 (2,709,486 in 2010 and 2,691,140 in 2009). Of these 2,727,782 households, we are able to match 2,494,621 households to a complete set of information from the different registers. The main missing information for the remaining households pertains to their educational qualifications, often missing on account of verification difficulties for immigrants.

To operationalize our analysis of refinancing, we begin by identifying households with a single fixed-rate mortgage. This is done in four steps. First we identify 953,099 households with a mortgage in 2009. Second, to simplify the analysis, we focus on households with a single mortgage throughout the sample period, leaving us with 702,834 households. Third, we focus on households with fixed-rate mortgages as these are the households who have financial incentives to refinance when interest rates decline. This leaves us with 281,698 households for the 2009 to 2010 refinancing decision, and 271,893 households for the 2010 to 2011 refinancing decision. Thus, in total we have 553,591 household observations across the two years. Finally, we expand the data to quarterly frequency using mortgage issue dates reported in the annual mortgage data, giving us a total of 2,146,395 quarterly refinancing decisions.[4]

We observe a total of 84,111 refinancings across the two years: 61,133 in 2010 and 22,978 in 2011. Of these, 39,878 refinancings were from fixed-rate to adjustable-rate mortgages, and 44,233 from fixed-rate to fixed-rate mortgages (or in a minority of cases to capped adjustable-rate mortgages which have similar properties to true fixed-rate mortgages). We treat both types of refinancings in the same way and do not attempt to model the choice of an adjustable-rate versus a fixed-rate mortgage.[5]

Collectively, our selection criteria ensure that the refinancings we measure are undertaken for economic reasons. Refinancing in our sample occurs when a household changes from one fixed-rate mortgage to another mortgage (whether it is fixed- or adjustable-rate) on the same property. Mortgage terminations that are driven by household-specific events, such as moves, death, or divorce, are treated separately by predicting the probability of mortgage termination, and using the fitted probability as an input into the Agarwal, Driscoll, and Laibson (2013) model of optimal refinancing. Note that this approach differs from that of the US prepayment literature, which seeks to predict all mortgage terminations regardless of their cause.

[4]This is less than the number of yearly observations times four (2,214,364), because some households refinance from a fixed-rate mortgage to an adjustable-rate mortgage, and drop out of the sample in subsequent quarters. Our imputation of quarterly refinancings will be incorrect if a mortgage refinances twice in the same calendar year (since only the second refinancing will be recorded at the end of the year), but we believe this event to be exceedingly rare.

[5]The comparison of adjustable- and fixed-rate mortgages is complex and has been discussed by Dhillon, Shilling, and Sirmans (1987), Brueckner and Follain (1988), Campbell and Cocco (2003, 2015), Koijen, Van Hemert, and Van Niewerburgh (2009), Johnson and Li (2014), and Badarinza, Campbell, and Ramadorai (2014) among others.

C. Descriptive statistics

Table 1 summarizes the characteristics of Danish fixed-rate mortgages, and households' propensity to refinance them. These characteristics are broken out by the annual coupon rate on the underlying mortgage bonds. In addition to the annual coupon, borrowers pay an administration fee to the mortgage bank. This fee is roughly 70 basis points on average, and depends on the loan-to-value (LTV) ratio on the mortgage, but is independent of household characteristics.

The average fixed-rate mortgage has an outstanding principal of DKK 905,000 (about $173,000 or EUR 118,000) and 23.3 years to maturity by the end of 2009. The outstanding principal corresponds to a loan-to-value ratio of 56.3% on average. From 2009 to 2010, 21.7% of all fixed-rate mortgages in our sample were refinanced, 10.0% to adjustable-rate and 11.7% to fixed-rate mortgages. As expected, the refinancing probability depends on the coupon rate of the mortgage bond underlying the old mortgage. For mortgages with a coupon of 3% and 4% the propensities to refinance are 3.9% and 5%, respectively.[6] For mortgages with a 5% coupon, which in 2009 accounted for roughly half of all fixed-rate mortgages, the propensity to refinance is 20.3%. The propensities to refinance are 55.6% and 43.7% for mortgages with coupon rates of 6% and 7% or more, respectively.

In 2011 the propensity to refinance was lower than in 2010. In total, only 8.5% of all fixed-rate mortgages were refinanced, 3.7% to adjustable-rate and 4.8% to fixed-rate mortgages. Still, we again see an increasing propensity to refinance as the coupon rate increases. For 3% coupon mortgages the propensity to refinance was a modest 3.1%, while the refinancing propensity for mortgages with a 6% coupon or higher lies between 11.7% and 15.9%.

In our empirical analysis we use ranks of income, financial wealth, housing wealth, education, and age rather than the actual values of these variables. Table 2 reports descriptive statistics on income, financial wealth, education and age for households with a fixed-rate mortgage. We report the underlying distribution for all households, and separately for refinancing and non-refinancing households, respectively. Across the distribution we find some consistent differences between refinancing and non-refinancing households. Income and housing wealth are slightly higher for refinancing households, while financial wealth is slightly higher for non-refinancing households. There are no systematic patterns for education (which as we will see results from the coarseness of our education measure), but refinancing households are younger across the entire age distribution.

Table 3 provides a more comprehensive set of descriptive statistics for all households with a fixed-rate mortgage, as well as a comparison of household characteristics between refinancing and non-refinancing households, measured in January of each year. Around 25% of all households consist of a single member, and 64% are married couples. The remainder

[6] Mortgage bonds with a 3% coupon were issued in 2005 during a previous period of relatively low mortgage rates. Most of the underlying mortgages for these bonds have a relatively low maturity of 10 years, or in some cases 20 years. These mortgages account for only a very small fraction of our dataset.

are cohabiting couples. Around 41% of the households have children living in the household. Table 3 also reports that 1% of the households got married within the last year, and that 4.2% of all households experienced the birth of a child within the last year. Around 3.6% of all households experience a negative health shock during the last year. We define a negative health shock as occurring whenever a member of a household receives medical treatment at a hospital (on an inpatient or outpatient basis) on 5 days or more during the last year, and received such treatment on fewer than 5 days in the year before.

We also have direct measures of financial literacy, defined as a degree in finance or professional training in finance for at least one member of the household. 4.6% of households are financially literate in this strong sense. A larger fraction of households, 12.9%, have members of their extended family (non-resident parents, siblings, in-laws, or children) who are financially literate.

Columns 2 to 7 of Table 3 report differences in household characteristics between refinancing and non-refinancing households in the full sample (column 2), the years 2010 and 2011 (columns 3 and 4), and subsamples of more highly educated (top quartile), married, and wealthier (top quartile) households (columns 5 to 7). A positive number means that the average characteristic is larger for refinancing households than for non-refinancing households. Column 2 shows that refinancing households are more likely to be married and less likely to be single, more likely to have children, to get married, and to experience the birth of a child, and less likely to have a negative health shock. Our measures of financial literacy are slightly higher for refinancing households. The ranked variables have the same patterns as in Table 2, implying that refinancers are younger and have higher income and housing wealth than non-refinancers, but lower financial wealth. We also find that refinancers are better educated, a pattern in the mean that was obscured by the cross-sectional percentiles reported in Table 2. The remaining columns of Table 3 show that these patterns are robust across subsamples. As we will see, similar patterns emerge in our more complex models of refinancing behavior that take account of refinancing incentives.

3 A Model of Refinancing Types

3.1 A mixture model of refinancing

Mixture models have a long history in statistics since Pearson (1894). A recent survey is presented in McLachlan and Peel (2000). Two current applications where mixture models are used to uncover decision rules are El-Gamal and Grether (1995) for Bayesian updating behavior, and Harrison and Rutström (2008) for utility specifications. We believe these models can be fruitfully applied to many problems in household finance.

A. Refinancing conditional on household type

Consider a model of mortgage choice in which the likelihood of observing a household i refinancing its fixed-rate mortgage at time t (the event $y_{i,t} = 1$) is determined by the type of the household h (a main target of our modelling efforts), which affects households' perceived financial incentives to refinance $I_h(z_{i,t})$, and a standard logistic distributed stochastic choice error $\epsilon_{i,t}$ following Luce (1959).

In the model, households of type h have a probability of refinancing given by:

$$p^h_{i,t}(y_{i,t} = 1|\nu_h, \beta_h) = p^h_{i,t}(\nu_h + e^{\beta_h} I_h(z_{i,t}) + \epsilon_{i,t} > 0). \tag{1}$$

In the above equation, $z_{i,t}$ contains both mortgage characteristics as well as household characteristics $s_{i,t}$, which together determine the household's perceived financial incentives to refinance. ν_h is the baseline probability of refinancing for households of type h. β_h captures the reaction to incentives, modelled as an exponent to ensure that households react non-perversely to incentives, as higher incentives always lead to an increase in the probability of refinancing for any value of β_h. It is possible to model both ν_h and β_h as functions of household characteristics $s_{i,t}$, and we attempt this in our empirical approach.

This specification implies that the likelihood contribution of each choice of household type h is:

$$\mathcal{L}^h_{i,t}(\beta_h, \nu_h) = \Lambda\left([2y_{i,t} - 1][\nu_h + e^{\beta_h} I_h(z_{i,t})]\right), \tag{2}$$

where $\Lambda(.)$ is the inverse logistic function, $\Lambda(x) = e^x/(1+e^x)$. For a single type, this model of household choice underlies the commonly used logit regression.

B. Household characteristics and mixing proportions

Our model considers households i as a mixture of proportions of these different types, each with a mixing weight $0 < \delta^h_i < 1$, constructed such that total weights for each household sum to one, i.e., $\sum_h \delta^h_i = 1$. Clearly, $\sum_i \sum_h \delta^h_i = N$, the number of households in the population.

We can now specify the likelihood contribution for household i as a finite mixture of proportions. This can also be interpreted as each household having a probability δ^h_i of being type h:

$$\mathcal{L}_{i,t}(\delta^h_i, \nu_h, \beta_h) = \sum_h \delta^h_i \mathcal{L}^h_{i,t}. \tag{3}$$

To ensure $\sum_h \delta^h_i = 1$ we construct the mixing proportions as

$$\delta^h_i = e^{\xi^h_i} / \sum e^{\xi^h_i}. \tag{4}$$

We allow for observable household characteristics to influence the relative weights on the different types, specifying $\xi_i^h = \chi_h' s_{it}$, where as before, s_{it} captures household demographic characteristics.

This leads to the household i log likelihood function over our sample specified as:

$$\ln \mathcal{L}(\chi_h, \nu_h, \beta_h) = \sum_t \sum_i \ln \left(\sum_h \delta_i^h \mathcal{L}_{i,t}^h \right) \tag{5}$$

3.2 Household types

A. Levelheads and woodheads

We define two different types of households, *levelheads* (type $h = L$) and *woodheads* (type $h = W$), who differ in their values of ν_h and β_h, as well as in the incentives $I_h(z_{i,t})$ that they perceive. Levelheads are approximately rational, while woodheads are inattentive to refinancing incentives (we borrow their name from Deng and Quigley 2012, and from mortgage industry slang).

Woodheads ignore incentives and refinance at a constant rate ν_W. To represent this behavior we set $I_W(z_{i,t})$ and β_W to zero. We do allow ν_W to vary with household demographic characteristics $s_{i,t}$.

Levelheads respond solely to the incentives that they perceive, and have no base rate of refinancing that is not contingent on incentives. To represent this behavior we set ν_L to zero. We estimate a levelhead sensitivity to incentives β_L, a fixed number that does not vary with demographic characteristics.

To illustrate the implications of this model, Figure 1 plots refinancing probabilities against incentives estimated in our Danish data set, using the simplest possible model in which demographic characteristics play no role. A zero incentive is defined as the interest saving at which a levelhead household has a 50% probability of refinancing. The levelhead refinancing probability, shown as a dot-long dashed line, is symmetric around the zero incentive, increasing rapidly from near zero at a negative incentive of about -1% to almost one at a positive incentive of about 1%. The woodhead refinancing probability, shown as a dot-short dashed line, is constant at slightly less than 1% regardless of the level of the incentive. We use a mixture model in which the estimated fraction of levelheads is 12%, so the overall estimated refinancing probability is the dashed line which is slightly less than 13% even at very high incentive levels. The empirically observed refinancing probability in our dataset is shown as the solid line.

B. Levelhead refinancing incentives

To measure the incentives to which levelheads respond, we follow Agarwal, Driscoll, and Laibson (ADL 2013). The incentive is the difference between the coupon rate on the mortgage bond corresponding to the current mortgage C_{it}^{old}, less the interest rate on a new mortgage Y_{it}^{new}, less a threshold level $O_h(z_{it})$:

$$I_h(z_{i,t}) = C_{i,t}^{old} - Y_{i,t}^{new} - O_h(z_{i,t}). \tag{6}$$

The function $O_h(z_{it})$ captures a variety of costs associated with refinancing. For levelheads, this function takes the fixed costs of refinancing into account, but in addition, it captures the option value of waiting for further interest-rate declines. We measure this option value in our empirical analysis using the second order approximation of ADL, i.e.,

$$O_L(z_{i,t}) \approx \sqrt{\frac{\sigma\kappa_{i,t}}{m_{i,t}(1-\tau)}\sqrt{2(\rho+\lambda_{i,t})}}, \tag{7}$$

where $m_{i,t}$ is the size of the mortgage for household i at time t, $\lambda_{i,t}$ is the expected exogenous rate of decline in the real value of the mortgage, and $\kappa_{i,t}$ is the fixed cost of refinancing. All of these parameters can in principle vary across households. Marketwide parameters include σ, the volatility of the interest rate, τ, the marginal tax rate that determines the tax benefit of mortgage interest deductions, and ρ, the discount rate.

Following ADL we define $\lambda_{i,t}$ and $\kappa_{i,t}$ as

$$\lambda_{i,t} = \mu_{i,t} + \frac{Y_{i,t}^{old}}{\exp(Y_{i,t}^{old} T_{i,t}) - 1} + \pi_t, \tag{8}$$

$$\kappa_{it} = f + \theta m_{i,t}. \tag{9}$$

Here $\mu_{i,t}$ can be interpreted as the probability of exogenous mortgage termination, Y_{it}^{old} is the yield on the household's pre-existing ("old") mortgage, $T_{i,t}$ is the number of years remaining on the mortgage, π_t is the inflation rate, f is the fixed cost of refinancing, and θ is the capital loss in basis points on the mortgage if it is refinanced. Our initial model uses a mixture of the recommended parameters in ADL and sensible values given the Danish context, i.e., $\sigma = 0.0074, \tau = 0.33, \rho = 0.05$, $\theta = 0$, and $f =$ DKK $10,000$ (about \$1,900 or EUR 1,300). π_t is calculated from the Danish consumer price index.

To allow for a more realistic measurement of $\lambda_{i,t}$, we estimate $\mu_{i,t}$ at the household level using additional data. Mortgage termination can occur for many reasons, including the household relocating, experiencing a windfall and paying down the principal amount, selling the property, or simply because the household ceases to exist because of death or divorce.

(We exclude refinancing from the definition of mortgage termination.) Without seeking to differentiate these causes, to estimate $\mu_{i,t}$ we use all households with a single fixed-rate mortgage, and estimate, for each year in the sample:

$$\mu_{i,t} = \Pr(\text{Termination}) = p(\mu' s_{i,t} + \epsilon_{i,t} > 0), \;\; \epsilon_{i,t} \; \sim \; N(0, \sigma). \tag{10}$$

using the same vector $s_{i,t}$ of household characteristics. We use the predicted termination probabilities from this model for each household i at time t to construct $\lambda_{i,t}$.

Figure 2 shows a histogram of the estimated mortgage termination probabilities, with a red line showing the position of the ADL suggested "hardwired" level of 10% per annum. The mean of our estimated termination probabilities is 11%, larger than the median of 8.4% because the distribution of termination probabilities is right-skewed. The standard deviation of this distribution is 8.7%.

Finally, we note that the ADL formula gives us the incentive for a household to refinance from a fixed-rate mortgage to another fixed-rate mortgage. Some households in our sample refinance from fixed-rate to adjustable-rate mortgages, implying that they perceive a new ARM as even more attractive than a new FRM. We do not attempt to model this decision here but simply use the ADL formula for all initially fixed-rate mortgages and refinancings, whether or not the new mortgage carries a fixed rate.

C. Dynamic effects

There are several reasons why the weights on different household types may depend on the date at which a household's mortgage was issued and the date at which the refinancing decision is observed. There may be pure time effects of the current date, for example if the population of mortgage borrowers becomes more aware of rational prepayment policy over time. There may be pure mortgage age effects if households avoid refinancing mortgages in the first few quarters after issue, or if they become less attentive to mortgages that have been outstanding for many years. The literature on prepayment modeling for US households, where demographic characteristics are not observed, pays particular attention to such mortgage age effects.

There may also be effects resulting from changes over time in the type composition of a particular cohort of mortgages. To understand this, consider two alternative extreme views about type assignment in our model. One extreme view is that each household draws a new type assignment each period, from a fixed distribution determined by its demographic characteristics. Given these characteristics, the probability of being a woodhead does not depend on the past behavior of the household; even if a household has failed to refinance for many periods, this does not make it any more likely to be a woodhead this period. According to this view, woodhead and levelhead behavior are temporary states, akin to being asleep or awake, rather than persistent conditions.

The opposite extreme view is that woodhead and levelhead behavior are permanent characteristics of individual households. If this is the case, then past behavior—and past incentives which drive levelhead behavior—should alter the conditional probability that a household is one or the other type. Specifically, during periods of positive refinancing incentives driven by declining interest rates, levelheads should refinance more rapidly than woodheads. With permanent type assignments, the remaining population of outstanding mortgages will have a higher fraction of woodheads in the future. Conversely, the fraction of woodheads declines during periods of negative refinancing incentives when only woodheads refinance.

Our ability to identify such dynamic effects is limited in several respects. There is the general problem that age, time, and cohort effects can never be identified in a panel without the application of some theoretical restrictions. And there is the more specific problem that we observe only two years of refinancing decisions. Given these limitations, we proceed informally by including in our vector of household characteristics a set of dummies for the quarter of mortgage issuance and the current quarter. (Dummies for the interaction of issuing quarter and current quarter add many coefficients but almost no explanatory power, so we exclude them.) We then interpret the patterns of coefficients on these dummies in the light of these theories of mortgage refinancing behavior.

D. Alternative household types

The framework we have developed above allows us to estimate alternative household types with relative ease. While we do not estimate these additional types in this draft, we briefly discuss a few potentially sensible alternative specifications here.

Staticheads, type $h = S$, differ from levelheads in that they do not consider the option value of future interest rate declines, but simply consider the fixed financial cost of refinancing, for example legal fees, as well as non-monetary costs of refinancing such as search and information processing costs, amortized over the life of the loan.

For such households, the threshold function is not the expression from ADL(2013), but instead $O_h(z_{it}) = O_S(z_{it})$, where:

$$O_S(z_{i,t}) = \frac{\kappa_{i,t}}{(1-\tau)m_{i,t}} \frac{1}{\left(\frac{1}{\rho} - \rho(1+\rho)^{T_{i,t}}\right)}. \tag{11}$$

Here $m_{i,t}$ is the size of the mortgage for household i at time t, $T_{i,t}$ is the number of years remaining on the mortgage, and $\kappa_{i,t}$ is the fixed cost of refinancing. All of these parameters in principle vary across households. Marketwide parameters include τ, the marginal tax rate that determines the tax benefit of mortgage interest deductions, and ρ, the discount rate.

Roundheads, type $h = R$, are more likely to refinance when the raw interest-rate spread is at a round number. Their refinancing probability can be written as:

$$p_{it}^{R}(y = 1|\nu_R, \beta_R, \mu_R) = p_{it}^{R}(\nu_R + e^{\beta_R}\Gamma(C_{it}^{old} - Y_{it}^{new}, \mu_R) + \epsilon_{i,t} > 0). \quad (12)$$

Here $\Gamma(.)$ is an indicator function for $C_{it}^{old} - Y_{it}^{new}$ being within μ_R of a round number, and e^{β_R} governs the stepwise increase in refinancing probability at that round number. This model can easily be generalized to allow different step sizes for different round-number values of the raw interest rate spread.

A variant of this model makes roundheads respond to the spread in coupon between old and new mortgage bonds. Since coupons are always lower than yields for newly issued bonds, to ensure that these bonds are issued at a discount, the coupon spread exceeds the raw interest-rate spread implying that roundheads of this type refinance before the raw interest-rate spread reaches a round number.

4 Empirical Results

4.1 Refinancing incentives

During our sample period Danish mortgage rates declined from the levels that had prevailed in the late 2000s, back to levels last seen in 2005. This pattern is illustrated by Figure 3, which plots the history of 30-year Danish mortgage rates from 2003. In the middle of 2010 the mortgage rate bottomed out just above 4%, before rising back above 5% in early 2011, and then declining again to below 4% later in the year, and even further through 2012. Throughout our data analysis, we treat each quarter as a single observation, and use the minimum weekly average mortgage rate during the quarter to calculate refinancing incentives.

Table 4 summarizes the cross-sectional distribution of refinancing incentives. The top panel of the table shows the interest rate spread between the coupon rate on the mortgage bond corresponding to the old mortgage, less the currently available mortgage rate. To ensure that we match old to new mortgages appropriately, we match using the remaining tenure on the old mortgage, within 10-year bands. That is, in each quarter, for mortgages with 10 or fewer years to maturity, we use the average 10 year mortgage bond yield to compute incentives, and for remaining tenures between 10-20 years (>20 years) we use the average 20 year (30 year) bond yield. These 10, 20, and 30 year yields are calculated as value-weighted averages of yields on all newly issued mortgage bonds with maturities of 10, 20, and 30 years, respectively.

The median interest spread computed in this fashion was 19 basis points in 2010 and

45 basis points in 2011, with wide cross-sectional variation. In 2010, for example, the 5th percentile of the interest rate spread was roughly –100 basis points, while the 95th percentile was 182 basis points.

The second panel of the table reports the Agarwal, Driscoll, and Laibson (ADL 2013) threshold that justifies refinancing. The median threshold is close to 95 basis points in both years, once again exhibiting wide cross-sectional variation, from 57 basis points at the 5th percentile to 196 basis points at the 95th percentile in 2010. The cross-sectional distribution of thresholds is right-skewed because, in the presence of fixed refinancing costs, a very high interest saving is needed to justify refinancing a small mortgage or a mortgage with only a few years left to maturity.

The third panel subtracts the ADL threshold from the interest rate spread for each mortgage to calculate the overall refinancing incentive perceived by rational (levelhead) mortgage borrowers. As the maximum threshold is extremely high, the minimum incentive is also represented by N/A since it will mechanically be extremely low. The median incentive was negative at –69 basis points in 2010 and –75 basis points in 2011, indicating that most mortgage borrowers should not have refinanced in these years. However, there is an important right tail of mortgages with positive refinancing incentives. The 95th percentile incentive was 75 basis points in 2010 and 69 basis points in 2011.

4.2 Errors of commission and errors of omission

A simple way to use these estimates is to calculate the incidence of refinancing mistakes. These fall into two main categories. Borrowing the terminology of Agarwal, Rosen, and Yao (2012), "errors of commission" are refinancings that occur at an interest-rate saving below the ADL threshold, while "errors of omission" are failures to refinance that occur above the ADL threshold.

Panel A of Table 5 reports the frequency of these two types of error. We define an error of commission as a refinancing with an interest rate saving below the ADL threshold less $k\%$, and an error of omission as a household-quarter where a refinancing does not occur even though the interest saving is above the ADL threshold plus $k\%$. The additional error cutoff level of k percentage points is introduced to take account of uncertainty in the ADL threshold. For a given k, households are classified as making errors of omission if they fail to refinance when incentives are greater than k, and errors of commission if they refinance with incentives less than $-k$, while incentives between $-k$ and k cannot generate either kind of error. In addition, we classify a refinancing as an error of commission only if the refinancing does not involve cash-out or maturity extension, since these alterations in mortgage terms could be sufficiently advantageous to justify refinancing even at a modest interest saving below the ADL threshold.

Table 5 shows that in our sample period, far more household-quarters have negative refinancing incentives (1,688,215 household-quarters in the case of $k = 0$) than have positive refinancing incentives (458,180 in the case of $k = 0$). However, within the large first group errors of commission are relatively rare, occurring slightly more than 1% of the time for error thresholds $k = 0$ or $k = 0.25$. Within the small second group errors of omission are extremely common, occurring 85%-90% of the time for low levels of k (0, 0.25, or 0.5) and even more often for higher levels of k.

While these numbers reflect a count of household-quarters rather than households, so that refinancing delays of a few quarters generate several errors of omission, the high incidence of errors of omission is nonetheless striking. It is consistent with the fact that we observe some large positive refinancing incentives in our dataset, which we could not do unless there had been errors of omission before the start of our sample period. To illustrate this point, Figure 4 plots the history of refinancing activity in relation to the currently available mortgage rate, dividing households by the coupon rate on their old mortgage bond (in the top panel) and the coupon rate on the new mortgage bond (in the bottom panel). The top panel illustrates the prevalence of errors of omission, as we can see a small fraction of households even in late 2011 still refinancing out of 7% mortgages despite the sharp dips in interest rates in 2010 and the overall low levels of interest rates. However, movements in interest rates do stimulate refinancing activity as we see from the refinancing spikes in the early part of 2010. These results support the focus of the literature on errors of omission, but also motivate the more careful econometric analysis of the determinants of refinancing that we undertake in the next section, distinguishing inertia and inattention using our mixture model.

Panel B of Table 5 relates errors of commission and errors of omission to demographic characteristics of households. The left hand panel of the table has an error cutoff of $k = 0$, while the right hand panel sets $k = 0.25$. In each column of the table, we report the mean difference for each of the demographic characteristics listed in the rows, between refinancing and non-refinancing households. Positive (negative) numbers under columns marked "Increases in Errors of Commission" signify demographic characteristics which are associated with shifts of household-quarters into (out of) such errors, and similarly positive (negative) numbers under columns marked "Reductions in Errors of Commission" signify demographic characteristics which are associated with shifts of household-quarters out of (into) such errors.

Almost all the household characteristics shown in Table 5 shift the refinancing probability in the same direction regardless of the incentive. Therefore characteristics such as marriage and education that reduce the incidence of errors of omission also increase the incidence of errors of commission. This suggests that household characteristics have an important effect on the baseline probability of refinancing, as well as the attention to incentives, a result that we indeed find when we estimate our more structural mixing model of refinancing behavior.

In Table 6, we attempt to quantify the costs of errors of omission in a simple fashion. A full analysis would require simulating interest rates, using either the interest rate process assumed by ADL or an empirical model of Danish interest dynamics. One would then track mortgages along simulated interest paths, calculating the mortgage interest and refinancing costs along each path for each possible refinancing threshold, and finally average across paths to measure the ex ante cost of a suboptimal refinancing policy. However, such an analysis would take us far afield from our empirical orientation in this paper.

Accordingly, we undertake a much simpler empirical exercise to calculate the realized excess interest paid on mortgages above the ADL threshold, net of refinancing costs. For each mortgage with an interest saving above the ADL threshold in each quarter, we calculate the difference between the interest paid on that mortgage, and the interest it would pay if it refinanced and rolled the fixed refinancing cost into the principal. We then divide by mortgage principal on these mortgages (in the top panel) or by total principal of all outstanding mortgages (in the bottom panel) and present averages for 2010, 2011, and the two years together.

Table 6 shows that along the realized path for Danish interest rates, errors of omission cost the households making them almost 1.5% on average in our sample period, if we assume a zero tolerance threshold k. As we increase k, we identify more serious errors and the costs rise, to 1.9% with $k = 0.25$, 2.1% with $k = 0.5$, and 4.0% with an extreme $k = 2$. Relative to the entire Danish mortgage market, these costs are 36 basis points with a zero k, 26 basis points with $k = 0.25$, 21 basis points with $k = 0.5$, and only 2 basis points if we go to the extreme $k = 2$. The decline in estimated costs relative to the entire market, as we increase k, is due to the fact that more extreme errors are less common, so while they have serious consequences for a few borrowers they are not as consequential in the Danish mortgage system as a whole.

While these numbers admittedly come from simple calculations conditional on a single path for interest rates, they suggest that errors of omission can have substantial costs. This finding is consistent with evidence reported in Miles (2004), Campbell (2006), Agarwal, Rosen, and Yao (2012), and Keys, Pope, and Pope (2014).

4.3 Simple logit models of refinancing

We begin by estimating a model that omits any information on the magnitude of the refinancing incentive, and simply uses household economic and demographic information to predict refinancing. In effect we treat all households as woodheads, and allow demographic variables to influence the refinancing coefficient v_W. We cluster standard errors at the household level and report coefficients along with indications of significance levels in the first column of Table 7.

Agarwal, Driscoll, Gabaix, and Laibson (2009) report that age has a nonlinear effect on many financial decisions, with financial sophistication increasing among younger people as they gain experience, and decreasing among older people perhaps because of cognitive decline. Education, income, and financial and housing wealth may also have different effects among less educated and poorer people than among better educated and richer people. We therefore want to allow for nonlinear effects of the ranked variables on refinancing probabilities. The appendix shows that results are quite similar whether we do this using a piecewise linear function with a kink at the median (achieved by adding the absolute value of the demeaned rank to the regression), or using a quadratic function (by adding twice the squared demeaned rank, a normalization that allows direct comparison of the coefficients in the two specifications). Accordingly we proceed with the quadratic specification and report these results in Table 7.

The demographic effects reported in the first column of Table 7 are broadly consistent with the simple differences in means discussed earlier in Table 3. However, certain effects are altered by the inclusion of all demographic variables simultaneously in this regression. For example, the effect of children in the family is now estimated to be insignificantly negative, whereas it was significantly positive in Table 3. In addition, there are interesting nonlinear effects of ranked variables. Older heads of household are less likely to refinance but the negative effect of age is much stronger among younger-than-average people than among older-than-average people. Education and income have hump-shaped effects on refinancing probability. This probability increases strongly with education and income among below-median households, but decreases among above-median households. Finally, the refinancing probability appears to decline virtually linearly with financial wealth, but it increases, albeit at a declining rate above the median, with housing wealth.

The second column of Table 7 adds dummies for the quarter of mortgage issuance, the current quarter, and the identity of the mortgage bank. These dummies add considerable explanatory power to the regression, increasing the pseudo-R^2 from 2.4% in the first column to 10.2% in the second column.[7] The issuing quarter dummies proxy for the refinancing incentive in this simple regression, as illustrated in the top panel of Figure 5. This panel shows the estimated coefficients on the issuing quarter dummies, with younger mortgages at the left and older mortgages at the right. The figure also shows the level of interest rates that prevailed in each issuing quarter (scaled on the right vertical axis), and the comovement of the two series is evident. However, some of the oldest mortgages in the sample have low issuing-quarter coefficients despite the high level of interest rates that prevailed when they were issued, consistent with the idea that refinancing is more sluggish among older mortgages (a phenomenon known as "burnout" in the US prepayment literature, see for example Kang and Zenios 1992, Stanton 1995, or Hall 2000).

The third column of Table 7 adds the level of the refinancing incentive to the logit regression, further increasing the pseudo-R^2 to 15.7%. This has a considerable effect on the coefficients estimated on the issuing quarter dummies, as shown in the bottom panel of Figure 5. The refinancing incentive soaks up the direct effect of the level of interest rates,

[7] The use of cross-product dummies that multiply issuing quarter by current quarter adds almost no explanatory power to the regression, so for parsimony we exclude these cross-terms. The mortgage bank dummies do contribute to the explanatory power of the regression, but owing to confidentiality restrictions and the small number of mortgage banks in the dataset, we do not report these coefficients.

and the pattern of issuing-quarter coefficients is now increasing among mortgages three years old or less, and then gradually declining. This nonlinear age effect is similar to that assumed in standard US prepayment models.[8] The figure also shows the fraction of each mortgage cohort's life that has had positive refinancing incentives (scaled on the right vertical axis). Mortgages that were issued in 2005 have had almost no experience of positive incentives, whereas those issued in 2002 or earlier have had a predominantly positive incentive history. There is a subtle but visible tendency for the issuing-quarter coefficients to be higher in the former group, and lower in the latter. This is consistent with the idea that the most attentive households remain in the 2005 mortgage cohort, but refinanced out of the 2002 mortgage cohort before the beginning of our sample period.

4.4 Mixture models

The demographic patterns in Table 7 are broadly robust to the inclusion of dummies for issuing quarter, current quarter, and refinancing incentives. However, these specifications do not allow any interaction between household characteristics and incentives. In Table 8 we estimate mixture models of household types that do allow such interactions. Once again we cluster standard errors at the household level and report coefficients along with indications of significance levels.

A. Model comparisons

The first column of Table 8 estimates a baseline model with a constant refinancing probability for woodheads and a constant proportion of levelheads (and therefore of woodheads) in the population. A low proportion of levelheads indicates that the population is relatively inattentive to incentives, and a low refinancing probability for woodheads indicates a high level of inertia, controlling for the level of attention.

The estimated model, illustrated earlier in Figure 1, implies that woodheads refinance each quarter with probability 0.8%, and 88% of the population are woodheads. The remaining 12% are levelheads, who refinance with probability 10% when the incentive is -0.88% (that is, when the raw interest spread is 0.88% lower than the ADL threshold), 25% when the incentive is -0.43%, 50% when the incentive is zero, 75% when the incentive is 0.43%, and 90% when the incentive is 0.88%. This model has a pseudo-R^2 statistic of 8.5%.

The next two columns of Table 8 allow demographic characteristics, as well as issuing-quarter, current-quarter, and mortgage issuer dummies, to shift first the woodhead refinanc-

[8] In particular, the increase in the dummies during the first three years of mortgage life is consistent with the PSA model established by the Public Securities Association, which has prepayments increasing linearly during the first 31 months of mortgage life and flat thereafter (Veronesi 2010, p. 296 and Figure 8.5). Note however that PSA and other US prepayment models apply to all prepayments, not just the refinancings we study in this paper.

ing probability only and then the proportion of levelheads only. We see very similar patterns of demographic effects on both these parameters. Demographic characteristics that change the baseline refinancing probability of woodheads also change the fraction of levelheads in the demographic group in the same direction: higher for single female and married households, lower for immigrant households, higher for financially literate households and households that are getting married or having children, higher for younger than average households, and so forth. Only a few effects, notably the nonlinear effects of financial and housing wealth, seem to be meaningfully different across these two models.[9]

The final two columns of Table 8 report a single model in which we allow household characteristics and mortgage dummies to influence both the woodhead refinancing probability and the proportion of levelheads simultaneously. This is the main model we use to interpret refinancing behavior among Danish households, and we now examine its properties in detail.

To illustrate the fit of this model, in Figure 6 we show the sample distribution of incentives, together with the observed refinancing probability at each incentive level. As previously discussed, most incentives are negative but the refinancing probability increases strongly around the zero level, peaking at around a 1% positive incentive. Very few observations have positive incentives above 1%.

In Figure 7 we show the observed refinancing probability together with the model's predicted refinancing probability and the estimated fraction of levelheads in the mortgage pools with each incentive level. The model captures the runup in refinancing probability well until an incentive of about 0.8%. Above this level it continues to track the spikes and dips in refinancing probability, but does not capture their magnitudes. The fraction of levelheads in the population is estimated to be largest among mortgages with incentives between -1% and 2% (the great bulk of the distribution illustrated in Figure 6), and lower in the extreme right tail of the incentive distribution.

Figure 8 plots the estimated coefficients on issuing-quarter dummies, for the woodhead refinancing probability in the top panel, and for the probability that a household is a levelhead in the bottom panel. The woodhead refinancing probability rises for about three years and then remains fairly flat on average, although with substantial fluctuations around that average. This shape is broadly consistent with the PSA model often used by investment practitioners to describe US prepayment behavior (Veronesi 2010).

[9] In the online appendix we estimate a model allowing demographic effects on the levelhead response to incentives. These effects are considerably weaker and generally have the opposite sign to those just discussed. When we allow demographic characteristics to affect only the response of levelheads to incentives, and not either the baseline refinancing probability or the proportion of levelheads, the model responds by flattening out the response to incentives among levelheads for demographic groups that have a high refinancing probability. In this indirect fashion it increases the estimated refinancing probabilities for such groups. However, the fit of this model (as measured by log likelihood or the pseudo R^2 statistic) is considerably worse than for the other two models. Accordingly, we proceed with a fixed parameter for the levelhead response to incentives.

The levelhead probability is generally declining with the age of the mortgage, but it rises substantially for mortgages issued between mid-2004 and mid-2006. These mortgages have experienced relatively few periods of positive refinancing incentives during their lifetime, as illustrated by the dashed line in the bottom panel of Figure 8. This pattern suggests that mortgage borrowers may have permanent characteristics, not perfectly captured by the demographic variables in the model, and that levelhead borrowers have disproportionately exited mortgage cohorts with positive past refinancing incentives.

B. Demographic effects

The demographic effects we estimate in our mixture model are broadly consistent with those discussed earlier using simpler statistics. To show more clearly the effects of the ranked variables—age, education, income, financial wealth, and housing wealth—we present a series of figures that show in the top panel the marginal estimated effect of the variable on the probability that a household is a levelhead (solid line) and on the woodhead refinancing probability (dashed line), and in the bottom panel the total effects of the variable (that is, the average estimated levelhead probability and estimated woodhead refinancing probability for households in each percentile of the distribution, taking account of the changes in all other demographic characteristics that are associated with the change in the ranked variable of interest).

Figure 9 shows that age has a negative effect on the levelhead probability among younger households. Controlling for other demographic characteristics, the youngest households are almost 3% more likely to be levelheads than middle-aged or older households. There is a very similar effect of age on the refinancing probability among woodheads, which is also about 3% higher than for middle-aged or older households. These effects are even stronger once we allow for changes in other demographic variables that are correlated with age: the bottom panel of the figure shows the levelhead probability declining by about 7% from the youngest households to the oldest households, with no flattening of the curve among older households. The woodhead refinancing probability also declines by about 7%, but this decline is concentrated among younger households.

Figure 10 shows a modest positive effect of education on the levelhead probability, particularly among households with less than average education, and regardless of whether other demographic characteristics are held fixed or allowed to vary in the typical fashion with education. The bottom panel of this figure appears somewhat coarse because large numbers of households have the same years of education, implying that the rank of education has mass at only a few points in the distribution.

Figures 11, 12, and 13 show that income has a hump-shaped effect on the levelhead probability, peaking at about the 75th percentile of income; financial wealth has a negative effect, particularly among poorer households; and housing wealth has a positive and almost linear effect. These patterns are consistent with a tradeoff between increased sophistication among households with higher income and wealth, and reduced significance of mortgage costs among households with extremely high income and high financial wealth relative to housing wealth. The woodhead refinancing probability is relatively little affected by income or housing wealth, but declines strongly with financial wealth among poorer households. This may reflect in part a greater tendency for households with little financial wealth to extract home equity through refinancing, even if the interest saving fails to reach the ADL threshold required by levelheads.

Finally, in Figure 14 we illustrate the fact that many of the estimated demographic effects shift the baseline refinancing probability and the proportion of levelheads in the same direction. The figure is a scatterplot for a subset of households, with the fitted demographic effects on inertia (baseline refinancing probability) on the horizontal axis and the fitted demographic effects on the levelhead proportion on the vertical axis. The correlation between these variables is 0.67 in the full dataset.

This finding can be described as follows. Danish household refinancing behavior cannot be described by a simple model in which only attention to incentives varies across households. As attention diminishes (captured here by a lower levelhead probability), households converge to a baseline refinancing probability that also depends on demographics, and which tends to be lower in demographic groups that pay less attention to incentives. In other words, inertia and inattention are positively correlated.

However, the correlation of these household attributes is not perfect. Some demographic effects operate differently on inertia and inattention: for example, single males have greater inertia but also pay greater attention to incentives, while families with children or negative health shocks have greater inertia but pay no less attention to incentives. Income increases attention among lower-income households, but has almost no effect on inertia. Because of such divergent demographic effects, we can reject a model that imposes proportionality on inertia and inattention, despite the positive cross-sectional correlation between these variables.

5 Conclusion

In this paper we have presented an analysis of sluggish mortgage refinancing behavior among Danish households. The Danish context is particularly advantageous for studying this type of household behavior because the Danish mortgage system places almost no restrictions on refinancing that does not involve cash-out, so households that pass up opportunities to substantially reduce their mortgage costs are not constrained, but are making mistakes in managing their finances. In addition, the Danish statistical system allows us to measure demographic and economic characteristics of households, and to use them to predict refinancing probabilities.

We distinguish between inattention (a reduced sensitivity to refinancing incentives) and inertia (a lower refinancing probability controlling for inattention). We capture these phenomena using a mixture model of stylized household types, "levelheads" who refinance rationally and "woodheads" who refinance at a fixed rate. Demographic characteristics can affect both the proportion of levelheads in the demographic group, a measure of attention, and the refinancing probability of woodheads, a measure of inertia. We find that many household characteristics move inertia and inattention in the same direction, so these attributes are positively correlated across households. Younger, better educated, and higher-income households have less inertia and less inattention. Interestingly, financial wealth and housing wealth have opposite effects, with the least inertia and inattention among households whose housing wealth is high relative to their financial wealth.

Both our methodology and our findings have relevance beyond the context of this paper. We believe that mixture models are a promising econometric method for estimating the prevalence of behavioral biases in the population. Our findings reinforce concerns that financial capabilities deteriorate late in life (Agarwal, Driscoll, Gabaix, and Laibson 2009) and that poorer households make worse financial decisions, contributing to inequality of wealth (Piketty 2014). The cross-sectional variation in refinancing behavior documented here is consistent with studies of other household financial mistakes in other countries (for example Campbell 2006 and Calvet, Campbell, and Sodini 2009b), suggesting that demographic characteristics of households can be used to estimate their financial capabilities across different countries and contexts.

A natural extension of our work, that we are currently undertaking for the next draft of this paper, is to enrich the description of irrational refinancing behavior to include statically optimal refinancing that ignores the option value of waiting to refinance, rule-of-thumb refinancing triggered by round numbers for interest rate savings, and other active behaviors such as reactions to attention-grabbing interest-rate movements. Our mixture model is well suited to investigate the nature and prevalence of refinancing behavior that is characterized neither by inertia nor by inattention, but by responses to inappropriate stimuli.

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Table 1: Characteristics of Danish Fixed Rate Mortgages

The average characteristics in Panel A (B) are calculated using mortgages taken by all households in Denmark with an unchanging number of members, and with a single fixed rate mortgage at the beginning of 2010 and 2011. The first five columns show the statistics broken out by the annual coupon rate on these mortgages, and the final column in each panel shows the statistics across all mortgages in each of the periods. The rows show, in order, the the number of observations; the fraction refinancing, i.e., the fraction of households who did not move house and refinanced their pre-existing mortgage; the principal remaining in Danish Kroner, i.e., the outstanding principal on the mortgage; the years remaining before the mortgage matures; and the loan-to-value (LTV) ratio calculated by the mortgage bank.

Panel A: 2010

	3% Coupon	4% Coupon	5% Coupon	6% Coupon	>6% Coupon	Total
Initial # of observations	8,054	79,929	141,610	44,590	7,515	281,698
Fraction refinancing	0.039	0.050	0.203	0.556	0.437	0.217
Fraction refinancing to ARM	0.013	0.024	0.108	0.218	0.153	0.100
Fraction refinancing to FRM	0.026	0.026	0.095	0.338	0.284	0.117
Principal remaining (Million DKK)	0.394	0.888	0.947	0.946	0.598	0.905
Years remaining on mortgage	7.849	21.425	24.552	25.371	22.281	23.256
Loan-to-value (LTV) ratio	0.242	0.506	0.595	0.640	0.462	0.563

Panel B: 2011

	3% Coupon	4% Coupon	5% Coupon	6% Coupon	>6% Coupon	Total
Initial # of observations	10,168	110,709	125,369	21,205	4,442	271,893
Fraction refinancing	0.031	0.041	0.114	0.159	0.117	0.085
Fraction refinancing to ARM	0.012	0.019	0.060	0.062	0.045	0.037
Fraction refinancing to FRM	0.018	0.021	0.053	0.097	0.095	0.048
Principal remaining (Million DKK)	0.479	0.978	0.883	0.591	0.321	0.875
Years remaining on mortgage	8.662	22.542	23.686	21.785	17.389	22.407
Loan-to-value (LTV) ratio	0.290	0.557	0.564	0.486	0.299	0.541

Table 2: Underlying Distribution of Ranked Variables

The percentiles of the distribution reported in the column headings are calculated across our sample of households in Denmark with a single fixed rate mortgage, pooling data over 2010 and 2011. The blocks of statistics are presented for income (total taxable income for each household in million DKK); financial wealth (the value of cash, bonds, stocks, and mutual funds less non-mortgage debt, in million DKK); Housing value (the value of properties, in million DKK); education (the number of years it takes to reach the highest level of education possessed by any individual in the household, where a rule of thumb is that 12 years is a high school diploma, 16 is a Bachelor's degree, 18 is a Master's degree, and 20 is a PhD); and age (measured in calendar years). Within each block of statistics, percentiles are calculated for all households, and separately for the sub-populations of refinancing and non-refinancing households. To preserve confidentiality, percentiles are calculated as the average of the five nearest observations to the percentile point.

	1%	5%	25%	Median	75%	95%	99%
				Income			
All	0.136	0.188	0.359	0.565	0.741	1.095	1.610
Refinancing	0.147	0.232	0.429	0.615	0.770	1.117	1.617
Non-refinancing	0.135	0.182	0.351	0.556	0.736	1.092	1.609
				Financial Wealth			
All	-1.305	-0.616	-0.179	0.031	0.225	0.879	2.068
Refinancing	-1.408	-0.728	-0.289	-0.051	0.124	0.655	1.658
Non-refinancing	-1.285	-0.595	-0.161	0.039	0.239	0.906	2.118
				Housing Wealth			
All	0.390	0.560	0.940	1.350	1.943	3.300	5.600
Refinancing	0.429	0.614	1.012	1.432	2.000	3.323	5.420
Non-refinancing	0.390	0.550	0.930	1.350	1.943	3.300	5.624
				Education			
All	7	7	12	12	16	18	20
Refinancing	7	9	12	12	16	18	20
Non-refinancing	7	7	12	12	16	18	20
				Age			
All	26	31	42	53	63	76	84
Refinancing	26	30	38	48	59	71	79
Non-refinancing	27	32	43	53	63	76	85

Table 3: Differences in Household Characteristics: Refinancing and Non-Refinancing Households

The first column shows the average of each of the characteristics reported in the rows, pooled across 2010 and 2011 for our entire sample. Columns 2 to 7 report the difference of means between refinancing and non-refinancing households, with a negative value indicating a lower mean for refinancing households. Differences are reported either unconditionally across the entire sample (Column "All"); conditional on sub-periods (Columns "2010" and "2011"); or conditional on other household characteristics (Columns "Educated, Married, Wealthy"). "Educated" households are defined as the upper 25% of the sample population. "Wealthy" households are those in the upper 25% of net financial wealth in the sample. The rows describe the characteristics; single households (male or female) have only one adult living at the address, and represent ~13% of the entire sample. "Married" households have two legally bound adults (including registered partnership of same-sex couples). "Children in family" means children are resident in the household. "Immigrant" takes the value of one if there is an immigrant in the household. "No educational information" indicates no information provided about this attribute. "Financially literate" takes the value of one if a member of the household has a degree in finance, or has had professional financial industry training. "Family financially literate" indicates if (non-household-resident) parents, siblings, in-laws, or children of the household are financially literate. "Getting married" indicates a change in marital status over the sample period. "Change to health" indicates when a member of the household spent more than 5 days in hospital within the last 12 months, and less than 5 days in hospital in the prior year. "Having children" indicates when households had a child within the last 12 months. "Rank of Age" is the rank of the age of the oldest person living in the household. "Rank of Education" is the rank of the best educated individual in the household. "Rank of Income (financial wealth, housing assets)" is the rank of the total income (financial wealth, housing assets) of the household. All ranks are computed each year across all households in the sample. Rank variables are normalized such that they take values between -0.5 and 0.5.

		Difference between Refinancing and Non-Refinancing Households					
	Average	All	2010	2011	Educated	Married	Wealthy
Single male household	0.128	-0.041***	-0.034***	-0.030***	-0.015***		-0.027***
Single female household	0.124	-0.029***	-0.029***	-0.026***	-0.022***		-0.015***
Married household	0.638	0.024***	0.021***	0.025***	0.004		0.031***
Children in family	0.406	0.102***	0.108***	0.079***	0.079***	0.095***	0.064***
Immigrant	0.072	-0.001	0.000	-0.001	-0.006***	-0.004***	0.002
No educational information	0.006	-0.003***	-0.002***	-0.003***		0.000***	-0.002***
Financially literate	0.046	0.006***	0.004***	0.011***	0.011***	0.004***	0.020***
Family financially literate	0.129	0.016***	0.015***	0.021***	0.023***	0.011***	0.034***
Getting married	0.010	0.009***	0.010***	0.006***	0.010***		0.004***
Change to health	0.036	-0.004***	-0.002***	-0.006***	-0.001	-0.005***	-0.006***
Having children	0.042	0.032***	0.033***	0.026***	0.036***	0.028***	0.019***
Rank of age	0.015	-0.087***	-0.098***	-0.070***	-0.079***	-0.075***	-0.047***
Rank of education	0.004	0.027***	0.029***	0.024***	0.000	0.017***	0.031***
Rank of income	0.008	0.056***	0.058***	0.049***	0.027***	0.033***	0.049***
Rank of financial wealth	0.009	-0.094***	-0.102***	-0.082***	-0.100***	-0.909***	-0.003***
Rank of housing value	0.010	0.029***	0.028***	0.027***	0.011***	0.019***	0.060***
Region North Jutland	0.124	0.000	0.004***	-0.006***	0.004***	0.000	-0.016***
Region Middle Jutland	0.241	0.023***	0.026***	0.015***	0.023***	0.021***	0.015***
Region Southern Denmark	0.228	0.002	-0.004***	0.018***	-0.003***	-0.001	-0.020***
Region Zealand	0.187	-0.015***	-0.012***	-0.023***	-0.012***	-0.014***	-0.004***
Region Copenhagen	0.220	-0.011***	-0.013***	-0.004	-0.012***	-0.006***	0.026***
# of observations	2,146,395	2,146,395	1,067,776	1,078,619	792,584	1,442,780	566,032

Table 4: Refinancing and Incentives

The percentiles of the distribution reported in the column headings are calculated across our entire sample of Danish households, pooling data over 2010 and 2011, as well as separately by year. The blocks of statistics refer to the interest rate spread in percentage points (defined as the coupon rate on the old mortgage less the yield on a newly available mortgage of roughly the same maturity); the threshold level above which refinancing is sensible, taking into account the option value of waiting, reported in percentage points, and calculated using the second order approximation in the Agarwal et al. (2013) formula; and the total incentive in percentage points, measured as the interest rate spread less the computed threshold level. Within each block of statistics, percentiles are calculated for all households separately for each variable, and separately for the sub-populations of refinancing and non-refinancing households. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point.

	1%	5%	25%	Median	75%	95%	99%
				Interest Rate Spread in Percentage Points			
All	-1.10	-1.01	-0.16	0.23	0.84	1.90	2.94
2010	-1.01	-1.01	-0.18	0.19	0.82	1.82	2.81
2011	-1.10	-1.10	-0.16	0.45	0.90	1.90	3.24
				Threshold Level in Percentage Points			
All	0.48	0.57	0.75	0.94	1.23	2.00	3.21
2010	0.47	0.56	0.74	0.93	1.21	1.95	3.00
2011	0.49	0.58	0.76	0.96	1.24	2.05	3.45
				Incentives in Percentage Points			
All	-2.87	-2.09	-1.22	-0.72	-0.08	0.72	1.38
2010	-2.77	-2.04	-1.15	-0.69	-0.05	0.75	1.32
2011	-2.98	-2.14	-1.27	-0.75	-0.12	0.69	1.46

Table 5: Errors of Commission and Omission

This table shows the incidence of errors of commission and omission, and the characteristics of households who commit errors of commission (refinancing when it is suboptimal), and errors of omission (not refinancing when it is optimal). We calculate the levels of incentives to engage in refinancing using the interest rate spread between the old and new mortgages less the Agarwal et al. function which quantifies the option-value of waiting, and we use these computed incentives (plus cutoff levels to control for noise in estimation) to classify errors. Each column shows cost estimates corresponding to the cutoff levels shown in the column header. For example, a cutoff level of 0 (0.25) corresponds to the interest rate spread being exactly equal to the computed Agarwal et al. threshold level (exceeding the Agarwal et al. threshold level by 25 basis points). Errors of commission (omission) which correspond to each cutoff are computed as the percentage of household-quarters with incentives below (above) the negative of the cutoff (the cutoff), who refinance (do not refinance). Panel A reports the incidence of errors of commission and omission for cutoff levels ranging from 0 to 2 percentage points. The bottom panel reports the mean difference for each demographic characteristic between refinancing and non-refinancing households who commit errors of commission and omission for two cutoff levels of 0 and 25 basis points. Positive (negative) numbers under columns marked "Increases in Errors of Commission" signify demographic characteristics which are associated with shifts of household-quarters into (out of) such errors, and similarly positive (negative) numbers under columns marked "Reductions in Errors of Commission" signify demographic characteristics which are associated with shifts of household-quarters out of (into) such errors.

Panel A: Incidence of errors of commission and omission

	Level of Cutoff						
	0	0.25	0.5	0.75	1	1.5	2.0
# Observations (Incentives < -Cutoff)	1,688,215	1,475,545	1,278,737	751,439	362,251	137,457	137,457
# Observations, refinancing	37,297	28,294	22,095	14,340	7,983	2,919	1,014
# Observations, cash out or extend maturity	15,743	12,224	9,715	7,356	4,878	1,921	791
# Observations, errors of commission	21,554	16,070	12,380	6,984	3,105	998	223
Fraction with error of commission	0.013	0.011	0.010	0.009	0.009	0.007	0.002
# Observations (Incentives > Cutoff)	458,180	252,336	152,097	100,844	61,309	17,434	6,287
# Observations, errors of omission	411,015	220,084	130,389	83,668	49,456	15,749	5,746
Fraction with error of omission	0.897	0.872	0.857	0.830	0.807	0.903	0.914

Table 5: Errors of Commission and Omission continued.

Panel B: Difference in Household Characteristics between Refinancing and Non-Refinancing Households

	Cutoff = 0		*Cutoff = 0.25*	
	Increases in Errors of Commission	*Reductions in Errors of Omission*	*Increases in Errors of Commission*	*Reductions in Errors of Omission*
# of observations	1,688,215	458,180	1,475,545	252,336
Single male household	-0.017***	-0.025***	-0.020***	-0.041***
Single female household	-0.015***	-0.020***	-0.017***	-0.031***
Married household	0.002***	0.008***	0.011***	0.028***
Children in family	0.055***	0.077***	0.064***	0.115***
Immigrant	-0.005***	-0.006***	-0.006***	-0.006***
Financially literate	0.002***	0.008***	0.002*	0.009***
Family financially literate	0.007***	0.019***	0.008***	0.023***
No educational information	-0.003***	-0.002***	-0.003***	-0.004***
Getting married	0.007***	0.009***	0.007***	0.010***
Change to health	-0.003***	-0.004***	-0.004***	-0.006***
Having children	0.025***	0.029***	0.026***	0.035***
Rank of age	-0.062***	-0.080***	-0.063***	-0.105***
Rank of education	0.003***	0.028***	0.006***	0.046***
Rank of income	0.018***	0.045***	0.025***	0.072***
Rank of financial wealth	-0.098***	-0.073***	-0.104***	-0.087***
Rank of housing value	0.005***	0.012***	0.016***	0.028***
Region North Jutland	0.004**	0.008***	-0.003	0.007***
Region Middle Jutland	0.019***	0.032***	0.014***	0.035***
Region Southern Denmark	0.018***	0.001	0.017***	-0.005**
Region Zealand	-0.018***	-0.020***	-0.014***	-0.014***
Region Copenhagen	-0.022***	-0.021***	-0.014***	-0.022***

Table 6: Costs of Errors of Omission

This table estimates the costs of errors of omission. We calculate the levels of incentives to engage in refinancing using the interest rate spread between the old and new mortgages less the Agarwal et al. function which quantifies the option-value of waiting, and we use these computed incentives (minus cutoff levels to control for noise in estimation) to classify errors. Each column shows cost estimates corresponding to the cutoff levels shown in the column header. For example, a cutoff level of 0 (0.25) corresponds to the interest rate spread being exactly equal to the computed Agarwal et al. threshold level (exceeding the Agarwal et al. threshold level by 25 basis points). Errors of omission occur for household-quarters with incentives above the cutoff, in which refinancing does not occur. The panel shows the cost of errors of omission calculated as the foregone annual interest saving (as a percentage of the outstanding mortgage balance) less the amortized fixed cost of refinancing given the available interest rates in each quarter of 2010 and 2011.

	Level of Cutoff						
	0	0.25	0.5	0.75	1	1.5	2.0
	Cost of errors of omission as % of outstanding mortgage						
All	1.48%	1.86%	2.09%	2.12%	2.50%	3.33%	4.01%
2010	1.42%	1.77%	1.99%	2.49%	2.31%	3.15%	3.70%
2011	1.57%	2.02%	2.27%	2.26%	2.87%	3.54%	4.34%
	Cost of errors of omission as % of all outstanding mortgages						
All	0.36%	0.26%	0.21%	0.15%	0.12%	0.04%	0.02%
2010	0.42%	0.31%	0.24%	0.18%	0.08%	0.04%	0.01%
2011	0.29%	0.21%	0.17%	0.12%	0.10%	0.04%	0.02%

Table 7: Logit Refinancing Models

This table shows results from simple logit specifications which seek to uncover the determinants of refinancing. The dependent variable takes the value of 1 if a household refinances in a given month and 0 otherwise. The models include non-linear transformations, f(x), of several of the ranked control variables, in addition to their levels x, defined by $f(x) = 2x^2$. As before, we estimate these specifications using all households in Denmark with an unchanging number of members, with a fixed rate mortgage in 2010 and 2011. The independent variables are indicated in the rows. The first set of variables is a set of dummy variables indicating the demographic status indicated in the row headers. The next set constitutes rank variables, which are normalized to take values between 0 and 1, and range between -0.5 and 0.5 once demeaned. All variables are described in greater detail in the header to Table 3. Model 1 is our baseline refinancing logit model with controls for demographics. Model 2 includes fixed effect controls for issuing quarter, current quarter, and mortgage issuer. Model 3 includes refinancing incentives as an additional regressor. Pseudo R^2 is calculated using the formula $R^2 = 1 - L_1/L_0$, where L_1 is the log likelihood from the given model and L_0 is the log likelihood from a model including only a constant. ***, **, and * indicate coefficients that are significant at the one, five, and ten percent level, respectively, using standard errors clustered at the municipality and year level.

	Model 1	Model 2	Model 3
Single male household	-0.097***	-0.015	0.055***
Single female household	0.065***	0.083***	0.129***
Married household	0.036***	0.070***	0.050***
Children in family	-0.015	0.003	-0.042***
Immigrant	-0.083***	-0.119***	-0.134***
Financially literate	0.048***	0.072***	0.087***
Family financially literate	0.018	0.044***	0.053***
No education information	-0.200***	-0.242***	-0.283***
Getting married	0.267***	0.175***	0.170***
Change to health	-0.003	-0.015	-0.026
Having children	0.210***	0.118***	0.122***
Region of Northern Jutland	0.125***	0.102***	0.185***
Region of Middle Jutland	0.145***	0.140***	0.217***
Region of Southern Denmark	0.099***	0.098***	0.177***
Region of Zealand	-0.016	-0.042***	-0.006
Demeaned rank of:			
Age	-0.670***	-0.358***	-0.241***
Length of education	0.062***	0.070***	0.058***
Income	0.218***	0.223***	0.084***
Financial wealth	-0.957***	-0.754***	-0.643***
Housing wealth	0.617***	0.671***	0.340***
Non-linear transformation f(x),where x is the demeaned rank of:			
Age	0.531***	0.362***	0.650***
Length of education	-0.288***	-0.330***	-0.407***
Income	-0.386***	-0.296***	-0.319***
Financial wealth	-0.090***	0.011	0.148***
Housing wealth	-0.331***	-0.273***	-0.017
Incentives			1.237***
Constant	-3.280***	-2.916***	-3.400***
Issuing Quarter Dummies	No	Yes	Yes
Current Quarter Dummies	No	Yes	Yes
Mortgage Issuer Dummies	No	Yes	Yes
Pseudo R2	0.024	0.102	0.157
Log Likelihood	-347,546.6	-319,618.6	-300,236.6
# of observations	2,146,395	2,146,395	2,146,395

Table 8: Mixture Models

In these specifications, the dependent variable continues to take the value of 1 for a refinancing in a given quarter, and 0 otherwise, using the same sample as in Table 7. In column 1 we estimate a simple baseline model with no demographics, in which we measure attention as the reaction to incentives computed as the interest rate spread between old and new mortgages less the Agarwal et al. (2013) function which quantifies the option value of waiting. Columns 2 and 3 estimate two separate specifications in which successively the woodhead refinancing probability and the probability of being a levelhead are allowed to depend on demographics as well as the dummies capturing issuing and current quarters, and mortgage issuers. Columns 4 and 5 present estimates from a mixture model in which both the woodhead refinancing probability and the probability of being a levelhead are allowed to depend on demographics and the above dummies. As before these models include non-linear transformations, f(x), of several of the rank control variables in addition to their levels, where $f(x) = 2x^2$. Pseudo R^2 is calculated using the formula $R^2 = 1 - L_1/L_0$, where L_1 is the log likelihood from the given model and L_0 is the log likelihood from a model including only woodheads with a constant refinancing probability. ***, **, and * indicate coefficients that are significant at the one, five, and ten percent level, respectively, using standard errors clustered at the municipality and year level.

	Baseline Model	*Models with Demographics Affecting:*		*Mixture Model*	
		Woodhead Refinancing Probability	Probability of Levelhead	Woodhead Refinancing Probability	Probability of Levelhead
Single male household		0.044	0.101***	-0.066*	0.095***
Single female household		0.156***	0.160***	0.111***	0.138***
Married household		0.086***	0.057***	0.097***	0.012***
Children in family		0.004	-0.030**	-0.058***	-0.003***
Immigrant		-0.214***	-0.149***	-0.210***	-0.132***
Financially literate		0.106***	0.103***	0.090*	0.074***
Family financially literate		0.060***	0.064***	0.051*	0.062***
No education information		-0.387***	-0.291***	-0.548***	-0.188***
Getting married		0.221***	0.189***	0.367***	0.185***
Change to health		0.007	-0.016	-0.081*	-0.007***
Having children		0.166***	0.128***	0.226***	0.098***
Region of Northern Jutland		0.220***	0.230***	0.059*	0.323***
Region of Middle Jutland		0.268***	0.266***	0.120***	0.325***
Region of Southern Denmark		0.216***	0.192***	0.206***	0.170***
Region of Zealand		-0.026	-0.015	-0.063**	0.014***
Demeaned rank of:					
Age		-0.449***	-0.307***	-0.282***	-0.323***
Length of education		0.070**	0.088***	-0.042	0.144***
Income		0.184***	0.184***	-0.100**	0.392***
Financial wealth		-1.222***	-0.704***	-1.387***	-0.319***
Housing wealth		0.818***	0.459***	0.630***	0.416***
Non-linear transformation f(x), x is the demeaned rank of:					
Age		0.713***	0.661***	0.942***	0.330***
Length of education		-0.651***	-0.484***	-0.654***	-0.298***
Income		-0.427***	-0.432***	-0.336***	-0.419***
Financial wealth		0.079*	0.190***	-0.004	0.175***
Housing wealth		-0.284***	-0.079**	-0.245***	-0.168***
Intercept: Woodhead Refinancing Probability	-4.860***	-4.236***	-5.013***	-6.156***	
Intercept: Response of Levelheads	0.937***	1.090***	0.853***	1.180***	
Intercept: Proportion of Levelheads	-1.954***	-2.502***	-2.375***	-2.361***	
Issuing Quarter Dummies	No	Yes	Yes	Yes	
Current Quarter Dummies	No	Yes	Yes	Yes	
Mortgage Issuer Dummies	No	Yes	Yes	Yes	
Pseudo R^2	0.085	0.121	0.149	0.157	
Log Likelihood	-323,535.8	-310,912.60	-301,204.5	-298,305.7	
Observations	2,146,395	2,146,395	2,146,395	2,146,395	

Figure 1: Baseline Mixture Model

This figure plots refinancing probabilities from the baseline mixture model estimated in Table 8 column 1 with homogeneous levelheads and woodheads. The solid line in the top panel of the figure shows the observed refinancing probability by incentive levels. The remaining lines show the model-predicted refinancing probabilities; (i) for woodheads (short dash and dot), (ii) for levelheads (long dash and dot), and finally (iii) the model predicted refinancing probability, which is the weighted average refinancing probability of woodheads and levelheads.

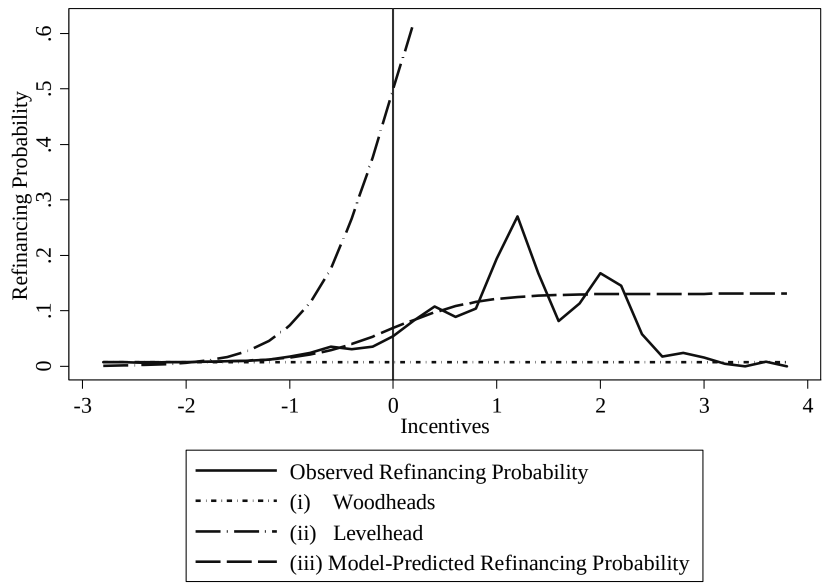


Figure 2: Histogram of estimated mortgage termination probabilities.

This figure shows our estimates of mortgage termination probabilities. To compute these estimates, we fit a simple probit model to realized mortgage terminations using all households with a single fixed-rate mortgage, conditioning the dummy variable for a termination on household characteristics. We plot the fitted values from this probit model, with a dark solid line at 10%, which is the Agarwal, Driscoll, and Laibson (2013) suggested "hardwired" value.

Figure 3: The history of 30-year Danish mortgage rates from 2003 to 2013

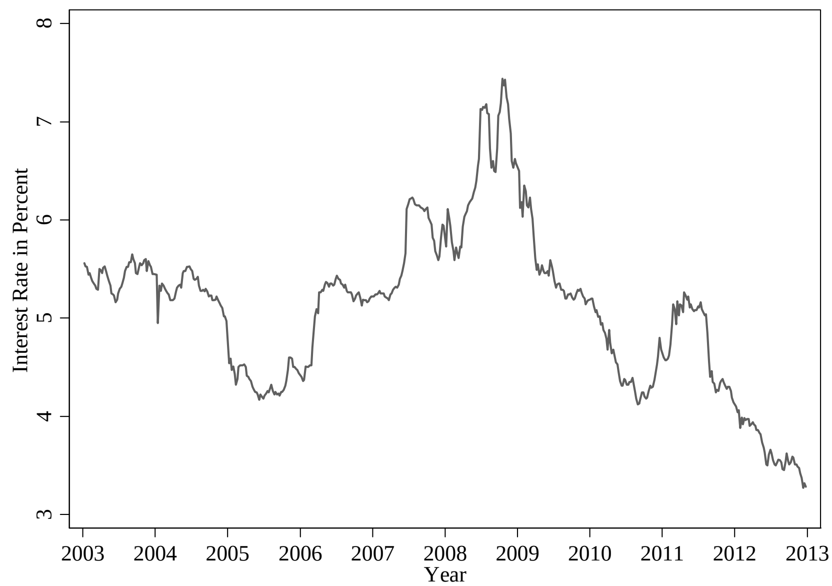


Figure 4: Refinancing activity by old and new mortgage coupon rates

This figure illustrates the history of refinancing activity in our sample of Danish fixed-rate mortgages. In each plot, the bars (left vertical axis) represent the number of refinancing households, while the solid line (right vertical axis) shows the history of the mortgage interest rate. The top panel shades each of the bars according to the coupon rate on the old mortgage from which households refinance. The bottom panel shades each of the bars according to the coupon rate on the new mortgage into which households refinance.

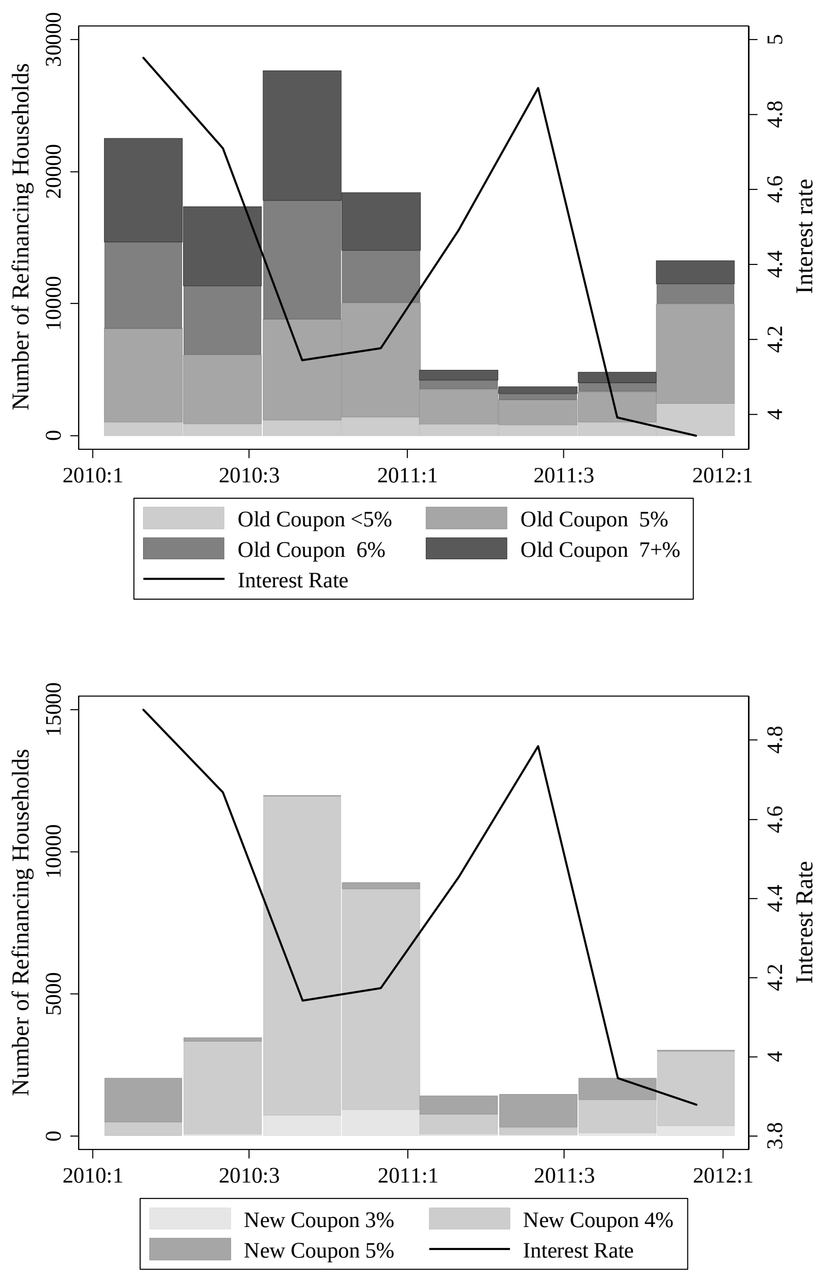
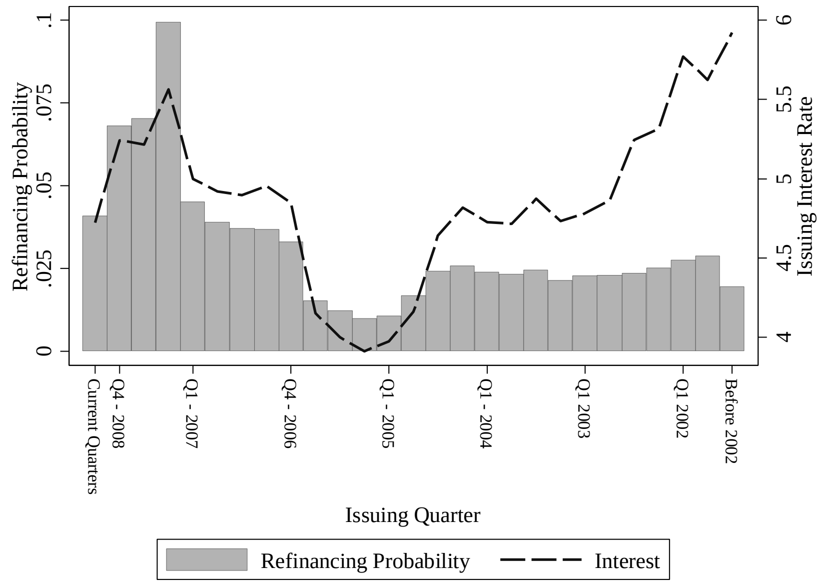


Figure 5: Estimated Issuing Quarter Effects in Logit Refinancing Models

This figure plots the predicted refinancing probability (left vertical axis) by issuing quarter (horizontal axis) using the estimated logit model 2 in Table 7, predicted at the mean for all other variables than the relevant issuing quarter. The first issuing quarter includes all issuing quarters within our refinancing period 2009-2011. The average coupon rate of issued bonds in each issuing quarter is plotted as a dashed line, scaled to the right vertical axis.



This figure plots the predicted refinancing probability (left vertical axis) by issuing quarter (horizontal axis) using model 3 in Table 7, predicted at the mean for all other variables than the relevant issuing quarter. Model 3 includes the refinancing incentive from the Agarwal et al. function. The first issuing quarter includes all issuing quarters within our refinancing period 2009-2011. The fraction of periods with positive incentives experienced by each issuing quarter is plotted as the dashed line, scaled to the right vertical axis.

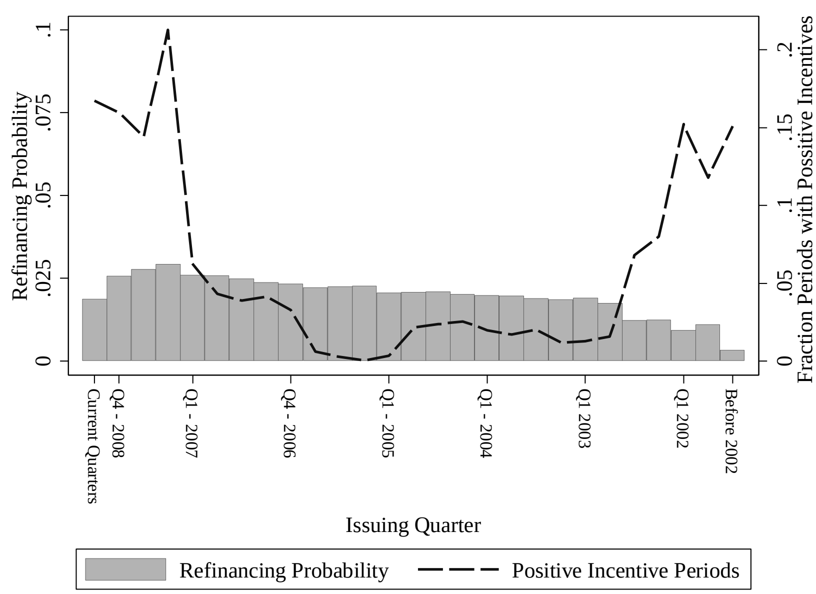


Figure 6: Refinancing and Incentives.

This figure plots the number of household-quarters in which we observe refinancing (left vertical axis) and the fraction of total household-quarters refinancing (right vertical axis) at each level of refinancing incentives shown on the horizontal axis. The plot uses 20-basis-point intervals for incentives.

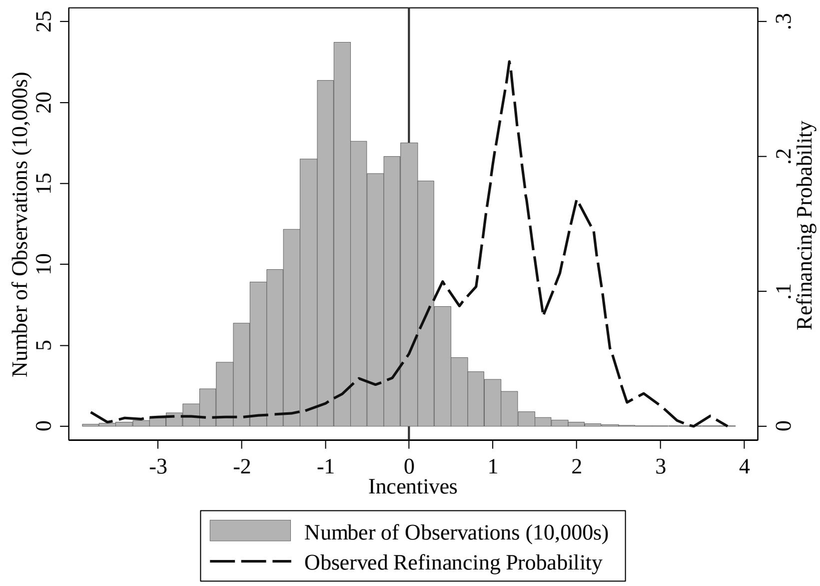


Figure 7: Refinancing probability by types, and the fraction of refinancing.

This figure plots refinancing probabilities from the complete mixture model with levelheads and woodheads estimated in Table 8, as a function of refinancing incentives constructed in various ways. The solid line in the top panel of the figure shows the observed (raw) refinancing probability, the dashed line with long dashes shows the model-predicted refinancing probability, and the dashed line with shorter dashes shows the fraction of households classified as levelheads in each period.

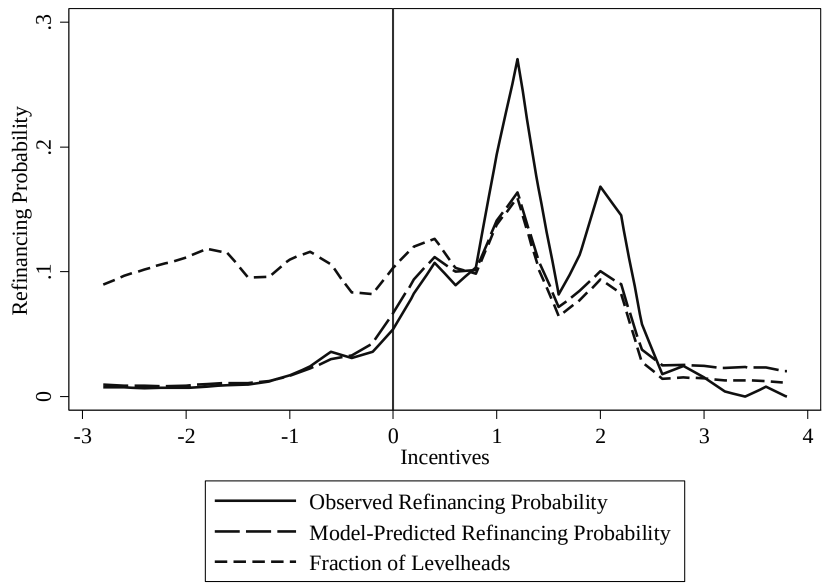


Figure 8A: Fitted Refinancing Probability by Issuing Quarter

This figure plots the predicted refinancing probability of woodheads (Y-axis) by Issuing Quarter (X-axis) using the estimated mixture model in Table 8, predicted at the mean for all other variables than the relevant issuing quarter. The first Issuing quarter is issuing quarters within our refinancing period 2009-2011. The fraction of periods with positive incentives for each issuing quarter is plotted as the line and uses the scaled on the right axis.

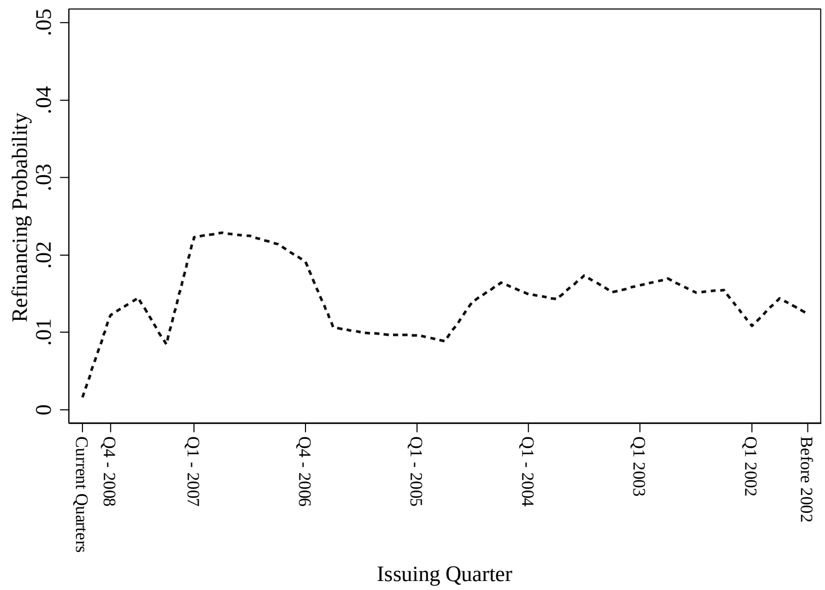


Figure 8B: Fitted Refinancing probability by Issuing Quarter, Heterogeneous Types

This figure plots the Levelhead Probability (left Y-axis) by Issuing Quarter (X-axis) using the estimated mixture model in Table 8, predicted at the mean for all other variables than the relevant issuing quarter. The second line plots the fraction of periods with positive incentives using the Agarwal function for each issuing quarter and uses the scale on the right axis. The first Issuing quarter is issuing quarters within our refinancing period 2009-2011.

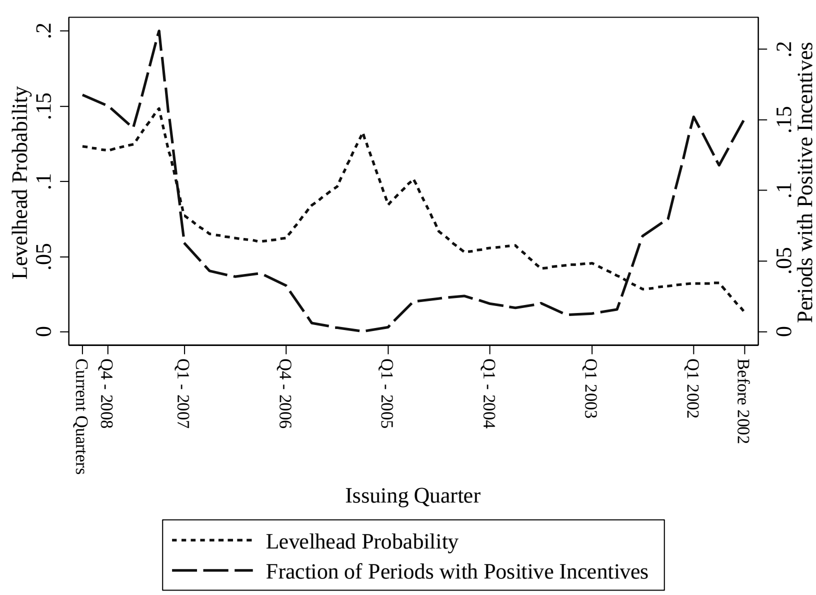


Figure 9A: Marginal Effects of Age on Levelhead Probability and Woodhead Refinancing Probability

This figure shows (i) the marginal change in the probability of being a levelhead and (ii) the marginal change in the woodhead refinancing probability, as functions of household age, fixing all other explanatory variables at their unconditional in-sample means, from the complete mixture model with levelheads and woodheads estimated in Table 8. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point, and lower (upper) limit as calculated at 1% (99%) level.

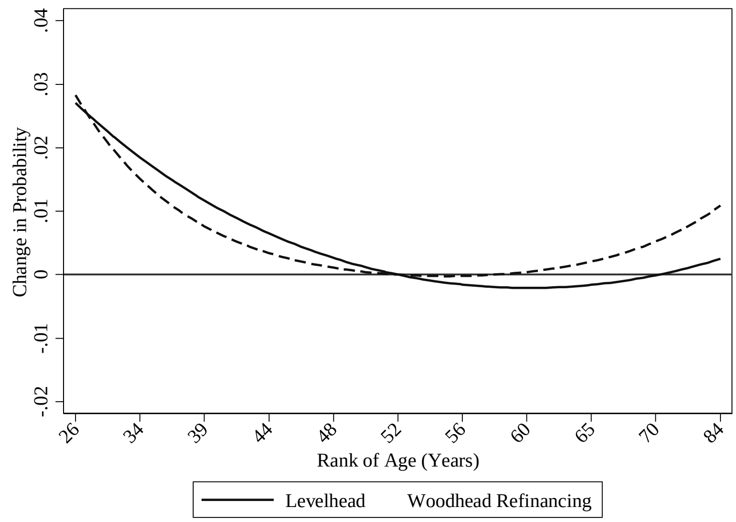


Figure 9B: Levelhead Probability and Woodhead Refinancing Probability as Functions of Age

This figure shows (i) an estimate of the total probability of being a levelhead and (ii) the total refinancing probability of woodheads, from the complete mixture model with levelheads and woodheads estimated in Table 8, at each rank of household age as shown on the X-axis. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point, and lower (upper) limit as calculated at 1% (99%) level.

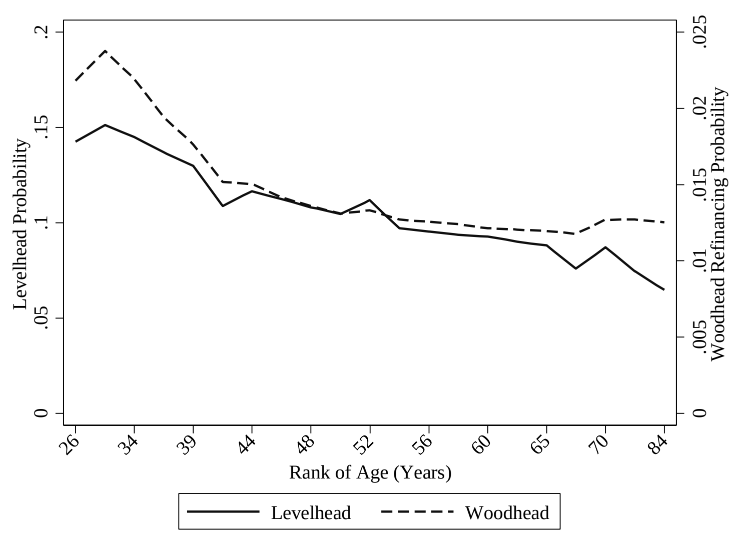


Figure 10A: Marginal Effects of Education on Levelhead Probability and Woodhead Refinancing Probability

This figure shows (i) the marginal change in the probability of being a levelhead and (ii) the marginal change in the woodhead refinancing probability, as functions of household education, fixing all other explanatory variables at their unconditional in-sample means, from the complete mixture model with levelheads and woodheads estimated in Table 8. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point, and lower (upper) limit as calculated at 1% (99%) level.

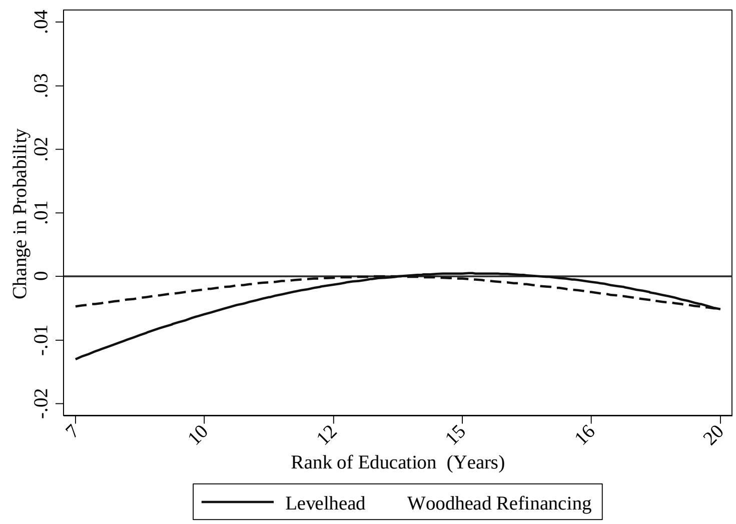


Figure 10B: Levelhead Probability and Woodhead Refinancing Probability as Functions of Education

This figure shows (i) an estimate of the total probability of being a levelhead and (ii) the total refinancing probability of woodheads, from the complete mixture model with levelheads and woodheads estimated in Table 8, at each rank of household education as shown on the X-axis. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point, and lower (upper) limit as calculated at 1% (99%) level.

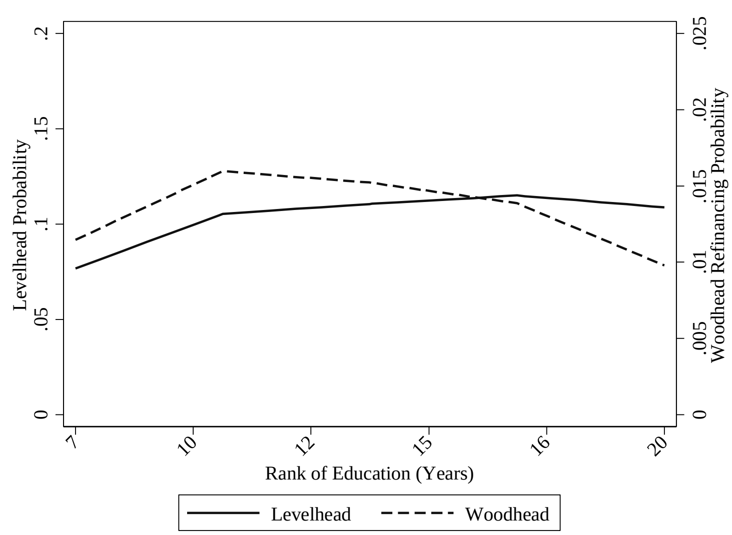


Figure 11A: Marginal Effects of Income on Levelhead Probability and Woodhead Refinancing Probability

This figure shows (i) the marginal change in the probability of being a levelhead and (ii) the marginal change in the woodhead refinancing probability, as functions of household income, fixing all other explanatory variables at their unconditional in-sample means, from the complete mixture model with levelheads and woodheads estimated in Table 8. The dotted lines are 5 and 95% confidence intervals.

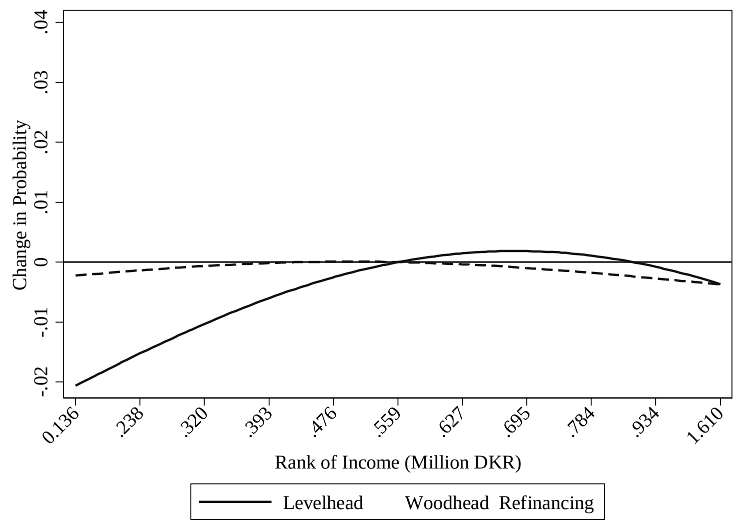


Figure 11B: Levelhead Probability and Woodhead Refinancing Probability as Functions of Income

This figure shows (i) an estimate of the total probability of being a levelhead and (ii) the total refinancing probability of woodheads, from the complete mixture model with levelheads and woodheads estimated in Table 8, at each rank of household income as shown on the X-axis. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point, and lower (upper) limit as calculated at 1% (99%) level.

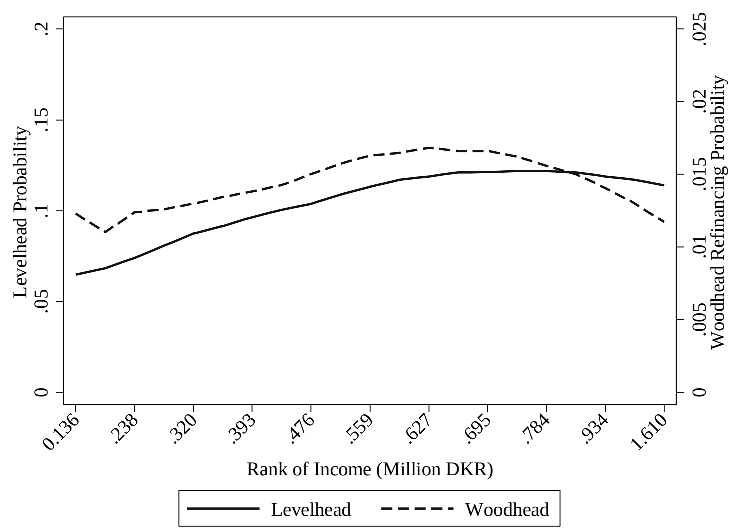


Figure 12A: Marginal Effects of Financial Wealth on Levelhead Probability and Woodhead Refinancing Probability

This figure shows (i) the marginal change in the probability of being a levelhead and (ii) the marginal change in the woodhead refinancing probability, as functions of household net financial wealth, fixing all other explanatory variables at their unconditional in-sample means, from the complete mixture model with levelheads and woodheads estimated in Table 8. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point, and lower (upper) limit as calculated at 1% (99%) level.

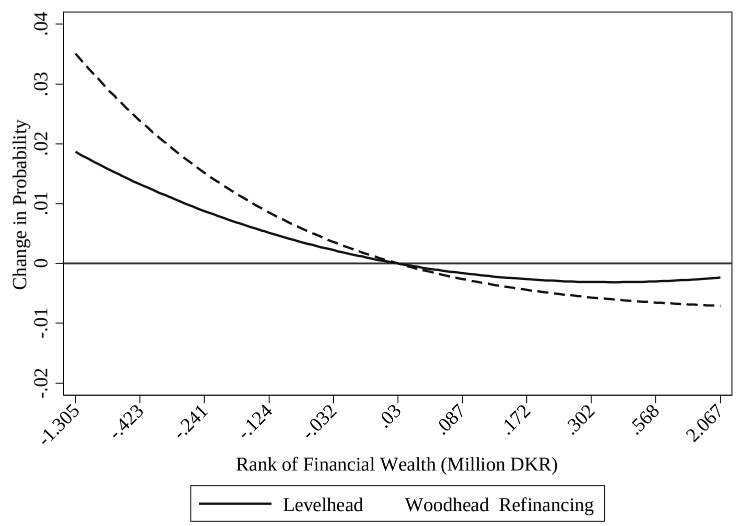


Figure 12B: Levelhead Probability and Woodhead Refinancing Probability as Functions of Financial Wealth

This figure shows (i) an estimate of the total probability of being a levelhead and (ii) the total refinancing probability of woodheads, from the complete mixture model with levelheads and woodheads estimated in Table8, at each rank of household net financial wealth as shown on the X-axis. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point, and lower (upper) limit as calculated at 1% (99%) level.

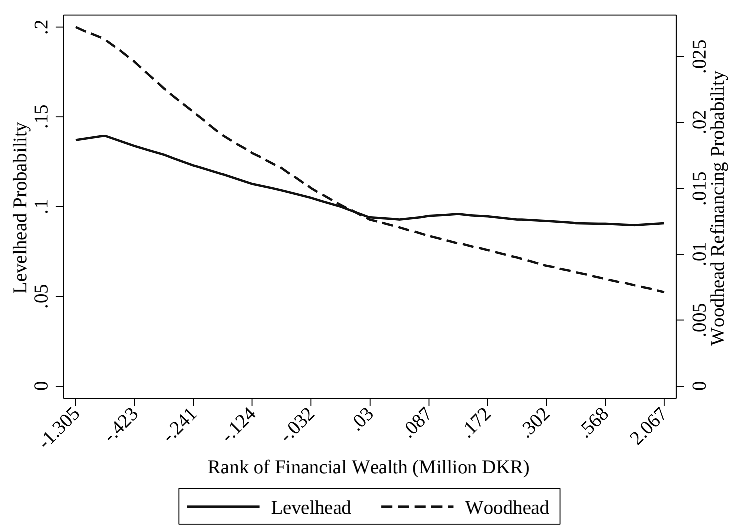


Figure 13A: Marginal Effects of Housing Wealth on Levelhead Probability and Woodhead Refinancing Probability

This figure shows (i) the marginal change in the probability of being a levelhead and (ii) the marginal change in the woodhead refinancing probability, as functions of household housing wealth, fixing all other explanatory variables at their unconditional in-sample means, from the complete mixture model with levelheads and woodheads estimated in Table 8. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point, and lower (upper) limit as calculated at 1% (99%) level.

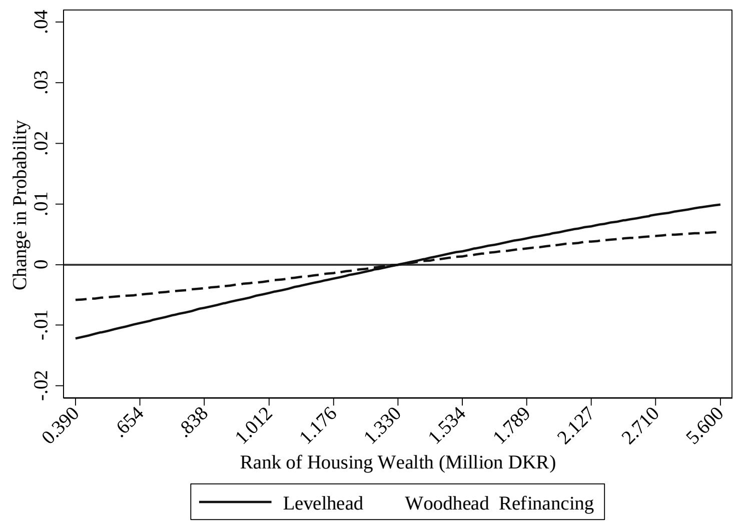


Figure 13B: Levelhead Probability and Woodhead Refinancing Probability as Functions of Housing Wealth

This figure shows (i) an estimate of the total probability of being a levelhead and (ii) the total refinancing probability of woodheads, from the complete mixture model with levelheads and woodheads estimated in Table 8, at each rank of household housing wealth as shown on the X-axis. To preserve confidentiality, percentiles are calculated using 5 nearest observations to the percentile point, and lower (upper) limit as calculated at 1% (99%) level.

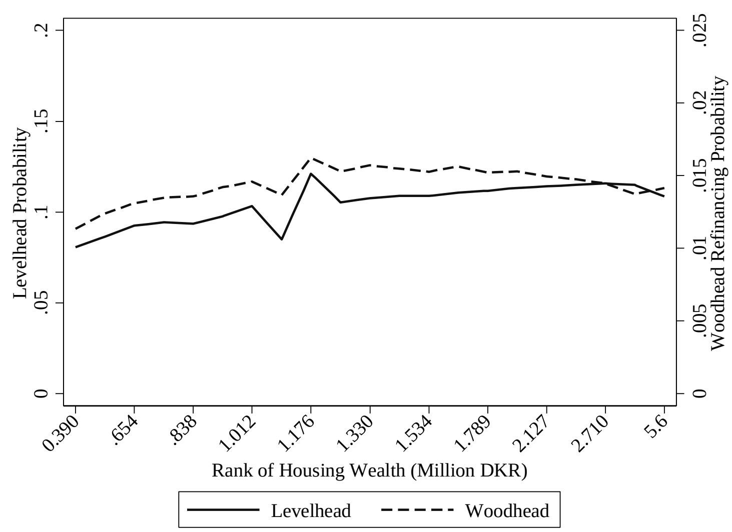


Figure 14: Proportionality of Mixing Proportions and Inertia

This figure plots the standardized fitted household demographic input into the probability of being a levelhead ($\xi = \chi' h$) on the Y-axis against the standardized fitted household demographic input into the woodhead refinancing probability (ν) on the X-axis from the complete mixture model with levelheads and woodheads estimated in Table 8. The plot is constructed using 1% of the sample. The solid line shows the fit of a univariate regression (with associated standard errors) to this cloud of points.