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

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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 finds that household characteristics affect both inattention (a low responsiveness of mortgage refinancing to financial incentives) and inertia (a low unconditional probability of refinancing). Many characteristics move inattention and inertia in the same direction, implying a high cross-sectional correlation of 0.76 between these two household attributes. Middle-aged and older households show greater inertia and inattention than young households. Education and income reduce both inertia and inattention, but the effect of education is greater among more educated households, while the effect of income is greater among poorer households. Housing and financial wealth have opposite effects on inertia, consistent with the view that households manage their mortgages more actively when housing is relatively more important to them.

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 2009).

Mortgage refinancing is one area where inertia appears to be particularly important. 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 (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 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 further 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 have no data on people who fail to refinance altogether.

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 (Campbell 2006, Schwartz 2006). US government efforts to relax refinancing constraints have been an important theme of US housing policy in the aftermath of the global financial crisis.

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 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 the high-quality Danish data to measure how household characteristics affect the responsiveness of households to refinancing incentives, as well as the unconditional or baseline refinancing probability. In this way we relate refinancing inertia to inattention, the inability of households to accurately perceive and act upon incentives.

Our work fits into a broader literature on the difficulties households have in managing their mortgage borrowing. Campbell and Cocco (2003, 2014) 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 (2011) 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, particularly for less sophisticated borrowers.

The organization of the paper is as follows. Section 2 explains the Danish mortgage system and household data. Section 3 presents a model of inattention and inertia. Section 4 estimates the model empirically, and section 5 concludes.

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 mortgage bond market is one of 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). In Europe, only Germany has a bigger market than Denmark in absolute terms.

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 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, 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 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 increase the principal balance of a mortgage. Danish borrowers can refinance their mortgages to reduce their interest rate and/or extend their loan maturity, without increasing their principal balance, even if their homes have declined in value so they have negative home equity. Related to this, fixed-principal refinancing 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 increasing the principal balance) 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.

Cash-out refinancing that increases mortgage principal does require sufficiently positive home equity and good credit status. For this reason, cash-out refinancing has been uncommon in Denmark in the period we examine since the onset of the housing downturn in the late 2000s.

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%.[2] Market yields, of course, fluctuate continuously. The discreteness of coupon rates at which bonds can be issued creates a peculiar situation. To raise, say, DKK 1 million (about $190,000 or EUR 130,000) for a mortgage, bonds must be issued with a face value that differs from DKK 1 million whenever the market yield differs from the coupon rate. Refinancing a mortgage requires buying the full face value of the bonds that were issued to finance the mortgage. This means that the incentive to refinance 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 the market yield on a mortgage bond (say 3.75%) is lower than the bond's coupon rate (say 4%). Then, the market value of the bond will be above its face value, so a DKK 1 million mortgage will be financed by issuing a bond with a market value of DKK 1 million, but a lower face value. Now consider what happens if market yields drop to 3.25%. Since borrowers can refinance by purchasing the original face value of 4% mortgage bonds at par and delivering them to the mortgage bank, funding the purchase by issuing new mortgage bonds with a yield of 3.25%, the incentive to refinance 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.

[2] More recently, bonds have been issued with non-integer coupons in response to the current low-interest-rate environment.

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, etc.) The mortgage data are available 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 cash (outside bank accounts), 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. Diagnosis and treatments are classified according to the WHO's ICD-10 system.[3]

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 2,727,791 households in 2011 (2,709,304 in 2010 and 2,691,078 in 2009). Of these 2,727,791 households, we are able to match 2,459,496 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 from overseas.

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 963,797 households with a mortgage in 2009. Second, to simplify the analysis, we focus on households with a single mortgage, leaving us with 743,117 households. Third, we focus on households with fixed-rate mortgages, giving us 366,104 households. Finally, we restrict the sample to households with a single mortgage in the subsequent year, leaving us with 278,426 households for the 2009 to 2010 refinancing decision, and 281,463 households for the 2010 to 2011 refinancing decision. Thus, in total we have 559,889 observations in the analysis per year, or 6,718,668 monthly decisions.

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.

[3]WHO's International Classification of Diseases, ICD-10, is the latest in a series that has its origin in the 1850s. WHO took over the responsibility for ICD at its creation in 1948. The system is currently used for mortality and morbidity statistics by all member states.

We realize that our simplifying assumptions result in attrition of the sample, and we hope to address this limitation in future versions of this paper by sensibly incorporating omitted households and mortgages.

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 917,000 (about $175,000 or EUR 120,000) and 23.5 years to maturity by the end of 2009. The outstanding principal corresponds to a loan-to-value ratio of 55.8% on average. From 2009 to 2010, 21.9% of all fixed-rate mortgages in our sample were refinanced. 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 4.7% and 5.1%, respectively.[4] For mortgages with a 5% coupon, which in 2009 accounted for roughly half of all fixed-rate mortgages, the propensity to refinance is 20.4%. The propensities to refinance are 56.3% and 48.7% 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 8.6% of all fixed-rate mortgages were refinanced. 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 3.7%, while the refinancing propensity for mortgages with a 6% coupon or higher lies between 16.2% and 14.0%.

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 only minor differences between refinancing and non-refinancing households. Income seems to be slightly higher across the distribution for refinancing households, and financial wealth appears slightly higher across the distribution for non-refinancing households, while there are no systematic patterns for education and housing value. We do see that refinancing households tend to be younger across the entire cross-sectional age distribution.

[4] 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.

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. Around 25% of all households consist of a single member, and 64% are married couples. The residual 11% are cohabiting couples. Around 42% of the households have children living in the household. Table 3 also reports that 1.3% of the households got married within the last year, and that 4.4% of all households had their first child within the last year. Around 3.4% 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, 12.8%, 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 educated, married, and wealthy 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 rather than single, more likely to get married and have their first child, and less likely to have a negative health shock. The remaining columns show that these patterns are robust across subsamples.

3 A Model of Inattention and Inertia

We specify a model of mortgage choice in which the probability that a household refinances its fixed-rate mortgage is determined by the financial incentive to refinance, as well as the level of attention that the household devotes to this incentive. The form of the model is

$$\Pr(\text{Refinancing}) = \Pr(\gamma' b_{it} + A(\delta' s_{it}) I(z_{it}) + \epsilon_{it}) > 0,\ \epsilon_{it} \ \sim\ N(0, \Sigma). \tag{1}$$

Here the vectors b_{it} and s_{it} contain characteristics of household i at time t. The characteristics in the vector b_{it} determine the baseline probability of refinancing, while those in the vector s_{it} shift attention—that is, they determine the responsiveness of the household to refinancing incentives. The vector $z_{i,t}$ contains characteristics of the household's mortgage at time t.

$A(.)$ is the index of attention for household i at time t, and $I(.)$ is the function determining the household's incentive to refinance. We use an exponential form for the attention function:

$$A(\delta' s_{it}) = \exp(\delta' s_{it}). \tag{2}$$

This is defined for all values of s_{it} and is always non-negative to avoid perverse reactions to incentives. As $A(s_{it}) \to 0$ the household ignores the incentive to refinance and its refinancing probability is determined by the baseline refinancing probability. As $A(s_{it}) \to \infty$ the household reacts sharply to any incentive; if the incentive is positive (negative), the household always (never) refinances.

We define the incentive to refinance as 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 $O(z_{it})$:

$$I(z_{it}) = C_{it}^{old} - Y_{it}^{new} - O(z_{it}). \tag{3}$$

The function $O(z_{it})$ captures a variety of costs associated with refinancing. These costs include fixed monetary costs, for example legal fees; non-monetary costs of refinancing such as search and information processing costs; and the option value of waiting for further interest-rate declines.

In our empirical analysis we define the threshold function to be the second order approximation of the option value in Agarwal, Driscoll, and Laibson (ADL 2013), i.e.,

$$O(z_{it}) \approx \sqrt{\frac{\sigma \kappa_{it}}{m_{it}(1-\tau)}} \sqrt{2(\rho + \lambda_{it})}, \tag{4}$$

where $m_{i,t}$ is the size of the mortgage for household i at time t, λ_{it} is the expected exogenous rate of decline in the real value of the mortgage, and κ_{it} 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 λ_{it} and κ_{it} as

$$\lambda_{it} = \mu_{it} + \frac{Y_{it}^{old}}{\exp(Y_{it}^{old} T_{it}) - 1} + \pi_t, \tag{5}$$

$$\kappa_{it} = f + \theta m_{it}. \tag{6}$$

Here μ_{it} 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_{it} 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 is calibrated to Danish data as follows: $\sigma = 0.0109, \tau = 0.33, \rho = 0.06$, $\theta = 0.01$, 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 λ_{it}, 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.

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:

$$\mu_{i,t} = \Pr(\text{Termination}) = \Pr(\mu' b_{it} + \epsilon_{it}) > 0, \ \epsilon_{it} \ \sim \ N(0, \Sigma). \tag{7}$$

using the same vector b_{it} 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 Agarwal et al. suggested "hardwired" level of 10% per annum. The internet appendix shows that our main results are qualitatively very similar if we use this hardwired mortgage termination probability rather than the estimated ones.

A hypothesis we explore in this paper is that household characteristics affect the baseline refinancing probability and the attention function in the same proportion. To test this hypothesis we set $b_{it} = s_{it}$ and estimate

$$\Pr(\text{Refinancing}) = \Pr(\gamma' b_{it} + A(k\delta' s_{it}) I(z_{it}) + \epsilon_{it}) > 0, \ \epsilon_{it} \ \sim \ N(0, \Sigma). \tag{8}$$

We calculate a likelihood ratio test from estimates of an unconstrained model setting $k = 1$, and a constrained model with a free k and $\gamma = \delta$ for all elements except the constants.

4 Empirical Results

4.1 Refinancing incentives and mistakes

A. 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 1, 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 4% later in the year. Throughout our data analysis, we treat each month as a single observation, and use the lowest mortgage rate during the month 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 month, 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 57 basis points in 2010 and -6 basis points in 2011, with wide cross-sectional variation. In 2010, for example, the 5^{th} percentile of the interest rate spread was –68 basis points, while the 95^{th} percentile was 188 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 150 basis points in both years, once again exhibiting wide cross-sectional variation, from 116 basis points at the 5^{th} percentile to 240 basis points at the 95^{th} 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. The median incentive was negative at –105 basis points in 2010 and –150 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 95^{th} percentile incentive was 40 basis points in 2010 and 0 basis points in 2011.

B. 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 an interest-rate saving below the ADL threshold, while "errors of omission" are failures to refinance that occur above the ADL threshold.

The top panel of Table 5 reports the frequency of these two types of error, conditional on the mortgage having an interest rate saving below the ADL threshold less $k\%$ (for errors of commission) or above the ADL threshold plus $k\%$ (for errors of omission). The additional error cutoff level of k percentage points is introduced to take account of uncertainty in the ADL threshold. That is, for a given k, incentives are computed as $C_{it}^{old} - Y_{it}^{new} - O(z_{it}) - k$.

The table shows that in our sample period, far more household-months have negative refinancing incentives (6,190,500 household-months in the case of $k = 0$) than have positive refinancing incentives (528,168 in the case of $k = 0$). However, within the large first group errors of commission are relatively rare, occurring about 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 around 95% 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-months rather than households, so that refinancing delays of a few months 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. These results provide some support for the focus of the literature (e.g. Campbell 2006 and Miles 2004) on errors of omission.

The second panel 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 $k = 0.25$. For households with incentives below or above $C_{it}^{old} - Y_{it}^{new} - O(z_{it}) - k$, we report the mean characteristics for households that do or do not refinance. Errors of commission are in the first column, while errors of omission are in the fourth column for each error cutoff.

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 structural refinancing model.

In Table 6, we attempt to quantify the costs of these errors of commission and omission in a simple fashion. The top panel of the table reports the percentiles of the distribution of interest rates in the two years 2010 and 2011 – there is substantial intra-year variation in both of these years, which we attempt to account for in our simple cost measurement exercise.

The middle panel of the table shows our cost estimates for errors of commission. For all refinancing households, in each year, and for each error cutoff level k, listed in the left-most column, we classify the refinancing decision as an error of commission if their incentives are below $C_{it}^{old} - Y_{it}^{new} - O(z_{it}) - k$.

We then compute the cost of these errors of commission as the additional, counterfactual interest rate saving that the household would have enjoyed if it had waited until a new, more favorable rate were available, or alternatively, if it had simply held on to the old mortgage.

Instead of using the realized path of mortgage rates following the refinancing decision, in order to construct a distribution of realistic counterfactuals, we look at the intra-year distribution of mortgage rates in each year of our sample, and evaluate costs of errors of commission at the $1^{st}, 25^{th}, 50^{th}, 75^{th}$, and 100^{th} percentile points of these distributions.

That is, for each of these counterfactual rates $Y^{counter}$, we measure the costs of errors of commission for refinancing households with incentives below $C_{it}^{old} - Y_{it}^{new} - O(z_{it}) - k$ as:

$$Cost_i^{Comm,k} = \max[Y_i^{new} - Y^{counter}, Y_i^{new} - Y^{old}, 0]$$

For example, the table shows that given a cutoff error level $k = 0.25$, if all households with incentives below $C_{it}^{old} - Y_{it}^{new} - O(z_{it}) - 0.25$ had refinanced at the within-2010 minimum interest rate $Y^{counter} = 4.08\%$, rather than into Y^{new}, their annualized interest cost would have been lower by an average of 36 basis points of their outstanding mortgage balances. In 2011, this is even higher, at 1% Unsurprisingly, this cost estimate decreases in the level of the counterfactual new interest rate, and increases with the error cutoff level, since a high cutoff isolates households that are paying more extreme new interest rates.

The bottom panel of the table shows the cost of errors of omission calculated as a percentage of the outstanding mortgage balance for households who do not refinance, despite incentives exceeding the cutoff value, calculated in a similar fashion to that for errors of commission.

That is, for each of these counterfactual rates $Y^{counter}$, we measure the costs of errors of omission for non-refinancing households with incentives above $C_{it}^{old} - Y^{counter} - O(z_{it}) - k$ as:

$$Cost_i^{Om,k} = \max[C_i^{old} - Y^{counter}, 0]$$

In this panel the cost estimates are higher than for errors of commission. The costs monotonically increase with the error cutoff level, since a high cutoff isolates households that are paying more extreme old interest rates. However they do not monotonically increase with the counterfactual interest rate, as the number of households classified as committing errors of omission declines with $Y^{counter}$.

Evaluated at the counterfactual maximum within-year interest rate for an error cutoff of 0.25, on an annualized basis, errors of omission cost households 2.31% of their outstanding mortgage balances in 2010, and 2.01% in 2011. While these numbers admittedly come from simple calculations with a number of embedded assumptions, they suggest that the costs of these mistakes are substantial.

Figure 3 illustrates 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. It is possible that some of these spikes represent errors of commission in response to attention-grabbing declines in interest rates.

These results motivate a more careful econometric analysis of the determinants of refinancing, distinguishing inertia and inattention using the model of the previous section.

4.2 Estimating inattention and inertia

A. Simple probit analysis of refinancing

We begin by estimating a version of equation (1) that omits any information on the magnitude of the refinancing incentive, and simply uses household economic and demographic refinancing to predict refinancing. These results are reported in Table 7.

We estimate three models that include the same dummy variables, but differ in their treatment of ranked variables (age, years of education, income, and financial wealth). 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 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.

Model 1 enters our ranked variables linearly. Model 2 adds the absolute value of the demeaned rank, a V-shaped function with the bottom of the V at the median household. In effect this allows a different slope on the ranked variables for households above and below the median. Model 3 replaces the absolute value of the demeaned rank with twice the squared demeaned rank. This is a U-shaped function with the bottom of the U at the median household, normalized in such a way that the average slope above the median and the average slope below the median are the same as in model 2 if the coefficients are equal. By comparing the coefficients estimated in model 2 and model 3, we can make sure that any nonlinear effects are robust to the exact manner in which nonlinearity is modeled. We do see some differences between model 1 and the two nonlinear models, but relatively minor differences between models 2 and 3. In the description of results below, we emphasize the results for model 3.

The main results in Table 7 are as follows. First, relative to baseline households (unmarried cohabiting couples), single male households are less likely to refinance, but single female and married couples are slightly more likely to refinance than cohabiting couples. The presence of children in the family reduces the refinancing probability. Second, discretionary life events (getting married or having a first child) increase the probability of refinancing, but health problems have little effect. Third, 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. Fourth, 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. Fifth, financial literacy in the household or the extended family slightly increases the refinancing probability. Sixth, 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. Finally, the coefficients are quite similar across model 2 and model 3 so the exact specification of nonlinear rank effects is immaterial for the results.

B. Models with incentives

The results in Table 7 could be misleading if households respond to financial incentives to refinance, and demographic characteristics are correlated with those incentives (perhaps through the date at which preexisting mortgages were taken out). In Table 8 we estimate some models that include simple incentive effects.

The columns headed "Baseline Probability" allow incentives to matter but they are constrained to do so equally across households. In other words the incentive effect is $\exp(\delta)$ for all households. We estimate δ to be about -1.03 in each of models 1, 2, and 3, implying that a 1% increase in the refinancing incentive increases the incentive-related term in equation (1) by $\exp(-1.03) = 0.35$. The coefficients on demographic variables are generally similar to the values reported in Table 7, implying that demographic effects are largely robust to consideration of incentives. Specifically, it remains true that (male) singles are somewhat less likely to refinance than couples, and people getting married or having their first child are more likely to refinance while people with health difficulties are no more or less likely to do so. One notable change, however, is that the inclusion of incentives now causes the effect of financial literacy on refinancing probabilities to be significantly positive.

Age continues to have a negative effect on refinancing probability, and its effect continues to flatten out at older ages. Education and income continue to look similar, with hump-shaped effects on refinancing probability. In the lower half of the distribution, these variables have strong positive effects on refinancing, but these effects reverse in the upper half of the distribution. Finally, financial wealth and housing wealth continue to have seemingly opposite effects in the baseline probability specification. Once again, these results are consistent across models 2 and 3, indicating robustness to the exact specification of nonlinearity.

The columns in Table 8 headed "Attention" allow household characteristics to affect the sensitivity of households to refinancing incentives. However characteristics are not allowed to affect the baseline refinancing probability, so all factors that diminish attention shrink the refinancing probability to a common value determined by the negative constant term in the regression. We find a mixture of results, some more intuitive than others. Education, for example, has a positive effect on attention in the upper half of the education distribution, and income has a positive and almost linear effect on attention. Financial wealth has a slight negative effect on attention in the upper half of the wealth distribution, but a strong positive effect in the middle of the wealth distribution, causing the function to look mildly hump-shaped. Housing wealth has a mild positive effect on attention in the lowest part of the wealth distribution. These findings may capture an effect discussed by Agarwal, Rosen, and Yao (2012), that borrowers pay more attention when their mortgages are relatively more important to them.

These differences between the results for the "inertia only" and "attention only" models suggest that we need a fuller specification in which we estimate both effects simultaneously, to capture the full range of factors determining refinancing behavior. Table 9 reports estimates of our full model that allows household characteristics to affect both the baseline probability of refinancing, and the response to incentives. Focusing on the results for model 3, we see that single females and married couples have a high refinancing probability and pay greater attention to incentives, relative to single males and cohabiting couples; children in the family reduce the baseline refinancing probability but not the attention to incentives; deliberate life events (marriage and having a first child) increase the baseline refinancing probability but not the attention to incentives; and financial literacy in the extended family increases both the baseline probability and the attention to incentives.

Turning to the ranked variables, many patterns are consistent across baseline refinancing probability and the response to incentives. Age reduces both of these, particularly among younger people; education increases both of them particularly (in the case of attention) among more educated people; and income increases both of them particularly among poorer people.

The separate estimation in Table 8 revealed differences in effects of financial and housing wealth on the baseline probability and on the attention to incentives. Table 9 shows that these differences persist when we account for both of these channels simultaneously. Financial wealth has a close-to-linear negative effect on the baseline probability, while housing wealth has a close-to-linear positive effect. However financial wealth has a hump-shaped effect on attention to incentives, which is greatest at intermediate levels of financial wealth, while housing wealth has a positive effect on attention in the lower half of the housing wealth distribution. Again, these results may reflect a tendency for households to pay more attention to mortgages when these are relatively more important to them (which will be the case when housing wealth is high and financial wealth is low), interacting with a tendency for financial wealth to correlate with general financial sophistication and attentiveness.

These patterns are summarized visually in Figure 4, which plots the refinancing probability (measured using model 3) against the incentive to refinance. Each panel of Figure 4 shows the curve for a typical household, and the curves for a household with all characteristics set to the average, except for the one of interest (the rank of age, education, income, financial, or housing wealth), which is varied between the 10th and the 90th percentile. Of course, these characteristics typically covary, but this is not taken into account in these figures, which vary the characteristics one at a time.

Figure 4 illustrates the strong effects that demographic household characteristics can have on refinancing probabilities in the presence of high incentives (at the right of the figure). Younger households respond much more strongly to high incentives than middle-aged or older households. Highly educated households respond much more strongly than households with average or below-average education. Lower-income households respond much less than middle- or high-income households. Housing wealth has a similar effect, with a lower response for households in the left tail of the housing wealth distribution. Financial wealth, however, has a nonlinear effect with the response higher for median households than for households in either tail of the financial wealth distribution.

Because Table 9 shows that many characteristics move the baseline refinancing probability and the response to incentives in the same direction, in Table 10 we estimate and test a specification in which the two sets of coefficients are proportional except for the constant terms. We do this for our linear model 1 and one of our two nonlinear models, model 3. We estimate the coefficient of proportionality to be about 0.54 in the nonlinear model, since the coefficients on attention are often about half as large as the baseline coefficients. However the proportionality restriction is strongly rejected.

A visual impression of the fit of a proportional model is provided in Figure 5. This figure shows a scatterplot of the estimated baseline function $\gamma' b_{it}$ against the estimated sensitivity to incentives $\delta' s_{it}$ (the argument of the attention function), estimated using model 3 in Table 9. There is a strong positive correlation of 0.76 between these two quantities, but the figure illustrates considerable variation away from a proportional model which would place all the points on a straight line.

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 (an increase in mortgage principal), 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 inertia (an unconditionally lower refinancing probability) and inattention (a reduced sensitivity to refinancing incentives). We find that many household characteristics move inertia and inattention in the same direction. Middle-aged and older households show greater inertia and inattention than young households. Education and income reduce both inertia and inattention, but the effect of education is greater among more educated households while the effect of income is greater among poorer households.

There are also some variables that have different effects on inertia and inattention, including the presence of children in the family and deliberate life events (marriage and the birth of a first child). Housing and financial wealth have roughly linear effects on inertia, with opposite signs, suggesting that households are more likely to manage their mortgages actively when their housing wealth is high relative to their financial wealth. However these variables have highly nonlinear effects on attention, with households in the middle of the financial wealth distribution paying greater attention to incentives than households in either tail of that distribution. Because of such effects, we can reject a model that imposes proportionality on inertia and inattention, even though the unconditional cross-sectional correlation between these variables is 0.76 in our full sample.

This version of our paper has some limitations. First, we have focused on interest-rate reduction as the motive for refinancing, and have not considered maturity extension. Second, we have ignored the distinction between FRM-to-FRM and FRM-to-ARM refinancing, treating the incentives from the Agarwal et al. function as appropriate for both types of refinancing. Third, we have modelled the probability of mortgage termination in a first step and used these estimated probabilities in our refinancing estimation, rather than modeling termination and refinancing jointly. We plan to address these issues in the next draft of the paper.

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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 in 2009 and 2010 (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 fraction refinancing, which is 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; the Loan-to-value (LTV) ratio calculated by the mortgage bank; and the number of observations in each coupon group and in the overall dataset.

Panel A: 2009- 2010

	3% Coupon	4% Coupon	5% Coupon	6% Coupon	>6% Coupon	Total
Fraction refinancing	0.047	0.051	0.204	0.563	0.487	0.219
Principal remaining (Millions DKK)	0.448	0.895	0.950	0.959	0.664	0.917
Years remaining on mortgage	8.538	21.621	24.674	25.641	23.846	23.537
Loan-to-value (LTV) ratio on mortgage	0.270	0.508	0.583	0.620	0.511	0.558
# of observations	6,807	79,792	141,274	43,895	6,658	278,426

Panel B: 2010- 2011

	3% Coupon	4% Coupon	5% Coupon	6% Coupon	>6% Coupon	Total
Fraction refinancing	0.037	0.046	0.114	0.162	0.140	0.086
Principal remaining (Millions DKK)	0.595	1.015	0.890	0.610	0.383	0.906
Years remaining on mortgage	10.189	23.327	23.881	22.298	19.395	22.989
Loan-to-value (LTV) ratio on mortgage	0.338	0.554	0.554	0.481	0.354	0.538
# of observations	9,885	120,013	127,133	20,793	3,639	281,463

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 refer to Income (defined as total taxable income for each household in million DKK), Financial wealth (defined as the value of cash, bonds, stocks, and mutual funds less non-mortgage debt, in million DKK), Housing value (defined as the value of properties, in million DKK), Education (defined as 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.

	Min	*5%*	*25%*	*Median*	*75%*	*95%*	*Max*
				Income			
All	-8.691	0.191	0.365	0.571	0.746	1.102	32.548
Refinancing	-2.945	0.234	0.433	0.617	0.770	1.118	15.338
Non-refinancing	-8.691	0.186	0.355	0.561	0.741	1.099	32.548
				Financial Wealth			
All	-143.905	-0.631	-0.190	0.025	0.215	0.864	214.073
Refinancing	-43.625	-0.761	-0.313	-0.068	0.113	0.648	65.713
Non-refinancing	-143.905	-0.600	-0.165	0.036	0.233	0.896	214.073
				Housing Wealth			
All	0.000	0.560	0.951	1.380	1.950	3.323	464.055
Refinancing	0.000	0.620	1.023	1.432	2.010	3.369	141.150
Non-refinancing	0.000	0.552	0.940	1.350	1.946	3.323	464.055
				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	20	31	42	52	62	75	99
Refinancing	20	29	38	47	59	71	96
Non-refinancing	20	32	43	53	63	76	99

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, computed using all households in Denmark with an unchanging number of members, with a fixed rate mortgage, pooling data over 2010 and 2011. Columns 2 to 7 report the difference of means between refinancing and non-refinancing households. A negative value indicates that refinancing households have a lower mean value. These 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) are defined as households with only one adult living at the address, and represent 13% of the entire sample. "Married" households are defined as households with two legally bound adults (which includes registered partnership of same-sex couples). "Children in family" is an indicator for households with resident children. Immigrant is an indicator which takes the value of one if there is an immigrant in the household. No educational information indicates households without any information provided about this attribute. "Financially literate" is an indicator which takes the value of one if someone in 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 a year, and less than 5 days in hospital in the prior year. "Having children" indicates when households have their first child. "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, and these 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	0.125	-0.031***	-0.030***	-0.028***	-0.013***		-0.024***
Single female household	0.121	-0.026***	-0.026***	-0.025***	-0.020***		-0.016***
Married household	0.641	0.023***	0.021***	0.024***	0.003		0.031***
Children in family	0.415	0.090***	0.093***	0.072***	0.070***	0.082***	0.056***
Immigrant	0.072	-0.001	-0.000	-0.002	-0.006***	-0.004***	0.002
No educational information	0.006	-0.002***	-0.002***	-0.003***		-0.000*	-0.002***
Financially literate	0.046	0.006***	0.004***	0.011***	0.011***	0.005***	0.020***
Family financially literate	0.128	0.015***	0.013***	0.020***	0.021***	0.010***	0.033***
Getting married	0.012	0.009***	0.010***	0.006***	0.011***	-0.000***	0.005***
Change to health	0.034	-0.004***	-0.002***	-0.006***	-0.001	-0.005***	-0.005***
Having children	0.044	0.033***	0.028***	0.025***	0.033***	0.025***	0.018***
Rank of age in years	0.014	-0.078***	-0.084***	-0.065***	-0.072***	-0.068***	-0.043***
Rank of education in years	0.001	0.024***	0.024***	0.022***	-0.000	0.014***	0.028***
Rank of income	0.005	0.049***	0.050***	0.046***	0.024***	0.029***	0.045***
Rank of financial wealth	0.004	-0.083***	-0.086***	-0.075***	-0.089***	-0.080***	-0.003***
Rank of housing value	0.005	0.025***	0.024***	0.025***	0.010***	0.015***	0.053***
Region North Jutland	0.123	0.001	0.005***	-0.006***	0.004**	0.002	-0.015***
Region Middle Jutland	0.242	0.022***	0.023***	0.016***	0.022***	0.020***	0.015***
Region Southern Denmark	0.228	0.003*	-0.004**	0.019***	-0.002	-0.001	-0.016***
Region Zealand	0.187	-0.015***	-0.012***	-0.024***	-0.012***	-0.014***	-0.005
Region Copenhagen	0.220	-0.011***	-0.013***	-0.005**	-0.013	-0.007***	0.021***
# of observations	6,718,668	6,718,668	3,341,112	3,377,556	2,366,472	4,291,992	1,674,012

Table 4: Cross-sectional Variation in Incentives

The percentiles of the distribution reported in the column headings are calculated across all households in Denmark with an unchanging number of members, with a fixed rate mortgage, 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, and separately for the sub-populations of refinancing and non-refinancing households.

	Min	*5%*	*25%*	*Median*	*75%*	*95%*	*Max*
				Interest Rate Spread in Percentage Points			
All	-2.11	-1.06	-0.26	0.36	0.82	1.82	7.55
2010	-2.06	-0.68	-0.06	0.57	0.88	1.88	6.76
2011	-2.11	-1.07	-0.40	-0.06	0.74	1.76	7.55
				Threshold Level in Percentage Points			
All	0.96	1.17	1.33	1.51	1.80	2.45	5.04
2010	0.96	1.16	1.32	1.50	1.78	2.40	4.94
2011	0.97	1.18	1.34	1.53	1.82	2.50	5.04
				Incentives in Percentage Points			
All	-5.96	-2.64	-1.85	-1.31	-0.69	0.27	5.22
2010	-5.37	-2.48	-1.66	-1.05	-0.55	0.41	4.45
2011	-5.96	-2.73	-2.03	-1.50	-0.88	-0.00	5.22

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 Agarwal et al. function, and use these computed incentives as optimal cutoff levels. For example, a cutoff level of 0 corresponds to the interest rate spread being exactly equal to the computed Agarwal et al. threshold level, and a cutoff of 0.25 means that the interest rate spread exceeds 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-months with incentives below (above) the cutoff, who refinance (do not refinance). The top panel reports the incidence of errors of commission and omission for cutoff levels ranging from 0 to 2 percentage points. The bottom panel reports the characteristics of households who commit errors of commission and omission for two cutoff levels of 0 and 25 basis points.

Incidence of errors of commission and omission

	Level of cutoff						
	0	0.25	0.5	0.75	1	1.5	2.0
# of observations with incentives < cutoff	6,190,500	6,002,468	5,590,729	4,880,301	4,156,015	2,782,087	1,371,540
Fraction with error of commission	0.010	0.009	0.008	0.007	0.006	0.004	0.003
# Observations, errors of commission	60,878	55,711	45,292	32,501	23,222	10,826	3,876
# of observations with incentives > cutoff	528,168	345,608	179,789	86,295	56,078	16,053	4,872
Fraction with error of omission	0.954	0.950	0.949	0.962	0.965	0.976	0.994
# Observations, errors of omission	503,749	328,306	170,587	82,988	54,089	15,673	4,844

Table 5: Errors of Commission and Omission, continued.

Household Characteristics Associated with Errors of Commission and Omission

	Cutoff = 0				**Cutoff = 0.25**			
	Incentives < Threshold		*Incentives > threshold*		*Incentives < Threshold*		*Incentives > threshold*	
	Refinance	*No Refinance*	*Refinance*	*No Refinance*	*Refinance*	*No Refinance*	*Refinance*	*No Refinance*
Single male household	0.103	0.127	0.072	0.102	0.101	0.127	0.061	0.095
Single female household	0.100	0.123	0.084	0.104	0.098	0.123	0.074	0.093
Married household	0.654	0.639	0.685	0.663	0.662	0.639	0.720	0.689
Children in family	0.487	0.410	0.549	0.467	0.487	0.411	0.577	0.490
Immigrant	0.069	0.071	0.075	0.078	0.068	0.071	0.076	0.077
Financially literate	0.054	0.046	0.045	0.038	0.055	0.047	0.046	0.040
Family financially literate	0.147	0.129	0.132	0.113	0.149	0.130	0.135	0.117
No education data	0.004	0.006	0.004	0.006	0.003	0.006	0.003	0.005
Getting married	0.019	0.011	0.023	0.015	0.019	0.011	0.021	0.014
Change to health	0.031	0.034	0.028	0.033	0.031	0.034	0.028	0.034
Having children	0.069	0.043	0.080	0.055	0.068	0.042	0.081	0.056
Rank of age in years	-0.055	0.017	-0.081	-0.005	-0.051	0.017	-0.077	-0.003
Rank of education in years	0.020	0.001	0.035	-0.003	0.021	0.001	0.045	0.004
Rank of income	0.043	0.002	0.079	0.026	0.044	0.003	0.102	0.043
Rank of financial wealth	-0.078	0.007	-0.074	-0.019	-0.076	0.008	-0.067	-0.019
Rank of housing value	0.030	0.004	0.028	0.006	0.035	0.005	0.048	0.024
Region North Jutland	0.122	0.123	0.130	0.125	0.121	0.123	0.127	0.123
Region Middle Jutland	0.263	0.241	0.267	0.245	0.261	0.242	0.260	0.245
Region Southern Denmark	0.233	0.227	0.224	0.235	0.233	0.227	0.219	0.230
Region Zealand	0.171	0.187	0.176	0.184	0.172	0.187	0.184	0.186
Region Copenhagen	0.221	0.222	0.203	0.211	0.213	0.221	0.210	0.216
# of observations	60,878	6,129,622	24,419	503,749	55,711	5,946,757	17,302	328,306

Table 6: Costs of Errors of Commission and Omission

This table shows the estimated cost of errors of commission and omission. We calculate the levels of incentives to engage in refinancing using the Agarwal et al. function, and use these computed incentives (plus cutoff levels to control for noise in estimation) to classify errors. Each row shows cost estimates corresponding to the cutoff levels shown in the leftmost row. 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) occur whenever a household refinances (does not refinance) when incentives are below (above) this threshold plus cutoff. The middle panel shows the estimated costs of errors of commission. These costs are evaluated using counterfactual mortgage rates into which refinancing could have occurred. These counterfactual interest rates are shown in the top panel, and drawn from the intra-year distribution of interest rates in 2010 and 2011. Each cell in the panel shows the annualized increase in interest payments (as a percentage of the outstanding mortgage balance) assuming refinancing occurred into the counterfactual rates labeled in the column header. The bottom panel shows the cost of errors of omission calculated as the foregone annual interest saving (as percentage of the outstanding mortgage balance) for households who do not refinance despite incentives exceeding the cutoff value, calculated in an analogous fashion to that for errors of commission, and again using the counterfactual interest rates shown in the column headers.

Counterfactual interest rates, drawn from intra-year realized values

	2010					**2011**				
	Min	*25%*	*Median*	*75%*	*Max*	*Min*	*25%*	*Median*	*75%*	*Max*
Interest rate (%)	4.079%	4.28%	4.79%	5.01%	5.19%	3.39%	4.21%	4.79%	5.13%	5.31%

Cost of errors of commission

	2010					***2011***				
Cutoff	*Min*	*25%*	*Median*	*75%*	*Max*	*Min*	*25%*	*Median*	*75%*	*Max*
0.00	0.367%	0.225%	0.064%	0.041%	0.038%	1.000%	0.308%	0.152%	0.113%	0.113%
0.25	0.357%	0.219%	0.069%	0.046%	0.044%	1.001%	0.313%	0.156%	0.117%	0.117%
0.50	0.390%	0.244%	0.081%	0.056%	0.056%	1.005%	0.355%	0.182%	0.139%	0.139%
0.75	0.459%	0.317%	0.114%	0.082%	0.081%	1.111%	0.436%	0.233%	0.181%	0.181%
1.00	0.519%	0.395%	0.172%	0.125%	0.125%	1.170%	0.506%	0.288%	0.226%	0.226%
1.50	0.497%	0.440%	0.322%	0.290%	0.290%	1.190%	0.571%	0.415%	0.364%	0.363%
2.00	0.598%	0.579%	0.538%	0.526%	0.526%	1.291%	0.747%	0.686%	0.665%	0.665%

Cost of errors of omission

	2010					**2011**				
Cutoff	*Min*	*25%*	*Median*	*75%*	*Max*	*Min*	*25%*	*Median*	*75%*	*Max*
0.00	2.160%	2.002%	2.036%	2.286%	2.158%	1.891%	2.124%	2.309%	2.457%	2.455%
0.25	2.217%	2.119%	2.507%	2.369%	2.305%	2.089%	2.280%	2.723%	2.712%	2.899%
0.50	2.361%	2.511%	2.600%	2.546%	2.702%	2.808%	2.601%	2.955%	3.228%	3.454%
0.75	2.869%	3.018%	2.808%	3.115%	3.724%	2.916%	3.256%	3.335%	3.757%	3.734%
1.00	3.230%	3.109%	3.454%	3.990%	3.915%	3.041%	3.455%	3.956%	3.958%	3.880%
1.50	3.577%	3.915%	4.399%	4.346%	4.284%	4.001%	4.323%	4.388%	4.354%	4.404%
2.00	4.949%	4.879%	4.777%	4.482%	4.862%	4.468%	4.921%	4.905%	4.708%	4.690%

Table 7: Refinancing: Simple Probit Specifications

This table shows results from simple probit 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. Model 1 estimates a probit, with no non-linear transformations of the independent variables. Models 2 and 3 include non-linear transformations, f(x), of several of the ranked control variables, in addition to their levels x. In Model 2, $f(x) = |x|$; and in Model 3, $f(x) = (\sqrt{2x})^2$. 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. ***, **, 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*	*Model3*
Single male household	-0.084***	-0.031***	-0.033***
Single female household	-0.017***	0.024***	0.023***
Married household	0.015***	0.017***	0.018***
Children in family	-0.025***	-0.006*	-0.007**
Immigrant	-0.038***	-0.031***	-0.031***
Financially literate	0.009	0.019***	0.021***
Family financially literate	0.007	0.007*	0.007*
No education data	-0.055***	-0.089***	-0.075***
Getting married	0.102***	0.094***	0.093***
Change to health	0.001	-0.003	-0.003
Having children	0.087***	0.073***	0.074***
Region of Northern Jutland	0.048***	0.047***	0.047***
Region of Middle Jutland	0.059***	0.055***	0.054***
Region of Southern Denmark	0.042***	0.037***	0.037***
Region of Zealand	0.002	-0.004	-0.005
Demeaned rank of:			
Age	-0.297***	-0.233***	-0.235***
Length of education	0.015***	0.023***	0.020***
Income	-0.008	0.077***	0.073***
Financial wealth	-0.323***	-0.330***	-0.329***
Housing wealth	0.203***	0.207***	0.211***
Non-linear transformation f(x),where x is the demeaned rank of:			
Age		0.214***	0.194***
Length of education		-0.119***	-0.094***
Income		-0.139***	-0.138***
Financial wealth		-0.043***	-0.035***
Housing wealth		-0.104***	-0.114***
Constant	-2.277***	-2.250***	-2.267***
Pseudo R^2	0.0147	0.0155	0.0155
Log Likelihood	-450501.74	-450104.52	-450120.39
# of observations	6,718,668	6,718,668	6,718,668

Table 8: Refinancing: Heterogeneous Baseline with Constant Attention, and Heterogeneous Attention with Constant Baseline

In these specifications, the dependent variable continues to take the value of 1 for a refinancing in a given month, and 0 otherwise, using the same sample as in Table 5. In columns 1, 3, and 5, we estimate a simple "Baseline" probit specification as in Table 4, but with the addition of "Incentives", measured using the Agarwal et al. (2013) formula. This approach calculates refinancing incentives as the difference between the annuitized option value of taking on the new mortgage, less the interest paid on the old mortgage. Columns 2, 4, and 6 estimate a specification in which these incentives are interacted with an "attention" function, holding fixed a baseline probability of refinancing. The level of attention is calculated by the function $A(\Delta' s) = \exp(\Delta' s)$, where Δ is the vector of estimated coefficients on the covariates in the vector *s*, reported in the rows, and described more fully in the header to Table 3. As before, Models 2 and 3 include non-linear transformations, f(x), of several of the rank control variables in addition to their levels; in Model 2, $f(x) = |x|$; and in Model 3, $f(x) = (\sqrt{2x})^2$. Pseudo R^2 is calculated using the formula $R^2 = 1 - L_1/L_0$, where L_1 (L_0) is the log likelihood from the unconstrained (constrained constant only) model. ***, **, 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**	
	Baseline Probability	*Attention*	*Baseline Probability*	*Attention*	*Baseline Probability*	*Attention*
Single male household	-0.050***	0.052***	0.008	-0.019	0.007	-0.016
Single female household	0.001	0.049***	0.050***	-0.014	0.049***	-0.012
Married household	0.007*	0.026**	0.012***	0.014	0.014***	0.008
Children in family	-0.054***	0.089***	-0.026***	0.046***	-0.025***	0.050***
Immigrant	-0.045***	0.054***	-0.035***	0.043***	-0.034***	0.044***
Financially literate	0.024***	-0.071***	0.031***	-0.070***	0.032***	-0.068***
Family financially literate	0.021***	-0.010	0.019***	-0.004	0.019***	-0.004
No education data	-0.071***	0.064	-0.132***	0.174***	-0.116***	0.156***
Getting married	0.085***	-0.155***	0.078***	-0.142***	0.078***	-0.140***
Change to health	0.003	-0.018	-0.004	-0.008	-0.004	-0.006
Having children	0.082***	-0.178***	0.060***	-0.138***	0.062***	-0.139***
Region of Northern Jutland	0.048***	-0.022*	0.055***	-0.027**	0.051***	-0.022*
Region of Middle Jutland	0.060***	-0.054***	0.063***	-0.060***	0.062***	-0.059***
Region of Southern Denmark	0.045***	-0.080***	0.049***	-0.090***	0.047***	-0.088***
Region of Zealand	-0.005	0.034***	-0.004	0.024**	-0.003	0.024**
Demeaned rank of:						
Age	-0.287***	0.190***	-0.217***	0.140***	-0.217***	0.150***
Length of education	0.036***	0.037**	0.038***	0.050***	0.036***	0.054***
Income	-0.057***	0.190***	0.033***	0.127***	0.035***	0.129***
Financial wealth	-0.294***	0.496***	-0.294***	0.509***	-0.290***	0.506***
Housing wealth	0.159***	-0.185***	0.175***	-0.177***	0.152***	-0.145***
Non-linear transformation f(x), x is the demeaned rank of:						
Age			0.293***	-0.370***	0.276***	-0.342***
Length of education			-0.159***	0.296***	-0.134***	0.261***
Income			-0.123***	0.077***	-0.127***	0.066**
Financial wealth			0.039***	-0.367***	0.040***	-0.404***
Housing wealth			-0.023**	-0.105***	0.014	-0.136***
Baseline Refinancing (Intercept)	-1.921***	-1.890***	-1.965***	-1.897***	-1.970***	-1.896***
Incentives (Intercept in Attention Function)	-1.033***	-1.054***	-1.031***	-0.897***	-1.030***	-0.917***
Pseudo R^2	0.011	0.003	0.012	0.004	0.012	0.004
Log Likelihood	-424107.16	-427339.95	-423705.79	-427173.92	-423703.63	-427003.48
Observations	6,718,668	6,718,668	6,718,668	6,718,668	6,718,668	6,718,668

Table 9: Heterogeneous Baseline with Heterogeneous Attention

In these specifications, the dependent variable continues to take the value of 1 for a refinancing in a given month, and 0 otherwise, using the same sample as in Table 5. This table shows the results of estimating three models (Models 1, 2, and 3). In each model, we allow for heterogeneous baseline probabilities of refinancing, conditional on household attributes (the first column under each model), *as well as* heterogeneous attention to incentives (the second column under each model). That is, pairs of columns now show results from the estimation of a single model. As before, "Incentives" are measured using the Agarwal et al. (2013) formula, which calculates refinancing incentives as the difference between the annuitized option value of taking on the new mortgage, less the interest paid on the old mortgage. The level of attention is calculated by the function $A(\Delta's) = \exp(\Delta's)$, where Δ is the vector of estimated coefficients on the covariates in the vector *s*, reported in the rows, and described more fully in the header to Table 3. As before, Models 2 and 3 include non-linear transformations, f(x), of several of the rank control variables in addition to their levels x; in Model 2, $f(x) = |x|$; and in Model 3, $f(x) = (\sqrt{2x})^2$. Pseudo R^2 is calculated using the formula $R^2 = 1 - L_1/L_0$, where L_1 (L_0) is the log likelihood from the unconstrained (constrained constant only) model. ***, **, 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**	
	Baseline Probability	*Attention*	*Baseline Probability*	*Attention*	*Baseline Probability*	*Attention*
Single male household	-0.061***	-0.030	0.002	-0.015	0.001	-0.012
Single female household	0.024***	0.094***	0.075***	0.098***	0.076***	0.102***
Married household	0.023***	0.058***	0.024***	0.046***	0.026***	0.044***
Children in family	-0.053***	0.002	-0.027***	-0.007	-0.026***	-0.005
Immigrant	-0.046***	-0.003	-0.037***	-0.007	-0.036***	-0.006
Financially literate	0.015*	-0.042*	0.025***	-0.031	0.027***	-0.027
Family financially literate	0.033***	0.039***	0.031***	0.041***	0.031***	0.041***
No education data	-0.066**	0.011	-0.111***	0.058	-0.097***	0.056
Getting married	0.093***	0.029	0.084***	0.025	0.084***	0.026
Change to health	-0.007	-0.043*	-0.012	-0.035	-0.011	-0.032
Having children	0.074***	-0.034**	0.053***	-0.027*	0.055***	-0.0261*
Region of Northern Jutland	0.067***	0.073***	0.077***	0.080***	0.073***	0.079***
Region of Middle Jutland	0.082***	0.077***	0.082***	0.068***	0.080***	0.067***
Region of Southern Denmark	0.043***	-0.010	0.045***	-0.018	0.044***	-0.019
Region of Zealand	0.010*	0.061***	0.008	0.045***	0.009	0.046***
Demeaned rank of:						
Age	-0.399***	-0.420***	-0.318***	-0.389***	-0.315***	-0.374***
Length of education	0.086***	0.198***	0.081***	0.174***	0.079***	0.176***
Income	0.005	0.237***	0.116***	0.321***	0.119***	0.328***
Financial wealth	-0.261***	0.115***	-0.272***	0.078***	-0.270***	0.073***
Housing wealth	0.187***	0.111***	0.219***	0.171***	0.198***	0.173***
non-linear transformation f(x), x is the demeaned rank of:						
Age			0.292***	-0.003	0.277***	0.008
Length of education			-0.113***	0.154***	-0.092***	0.144***
Income			-0.184***	-0.215***	-0.196***	-0.243***
Financial wealth			-0.057***	-0.394***	-0.066***	-0.432***
Housing wealth			-0.089***	-0.250***	-0.051***	-0.234***
Baseline Refinancing (Intercept)	-1.949***		-1.948***		-1.965***	
Incentives (Intercept in Attention Function)		-1.135***		-0.949***		-0.998***
Pseudo R^2		0.013		0.014		0.014
Log Likelihood	-423258.97		-422735.06		-422728.92	
# of observations	6,718,668		6,718,668		6,718,668	

Table 10: Test of Proportionality of Heterogeneous Baseline with Heterogeneous Attention

In these specifications, the dependent variable continues to take the value of 1 for a refinancing in a given month, and 0 otherwise, using the same sample as in Table 6. This table shows the results of estimating two models (Models 1 and 3). Unlike the unconstrained estimation in Table 9, here we estimate a constrained model in which all coefficients in the attention function are constrained to be proportional to the coefficients on the same variables in the baseline. The estimated coefficient of proportionality is reported in a row labeled as such towards the bottom of the table. The columns labeled "deviation" show the simple difference between the coefficients in the constrained model (reported in the first and third columns under each model) and the unconstrained model estimates from Table 9. As before, "Incentives" are measured using the Agarwal et al. (2013) formula, which calculates refinancing incentives as the difference between the annuitized option value of taking on the new mortgage, less the interest paid on the old mortgage. The level of attention is calculated by the function $A(\Delta' s) = \exp(\Delta' s)$, where Δ is the vector of estimated coefficients on the covariates in the vector s, reported in the rows, and described more fully in the header to Table 3. As before, Model 3 includes non-linear transformations, $f(x)$, of several of the rank control variables in addition to their levels x with $f(x) = (\sqrt{2x})^2$. ***, **, 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 3**			
	Baseline Probability	*Deviation*	*Attention*	*Deviation*	*Baseline Probability*	*Deviation*	*Attention*	*Deviation*
Single male household	-0.059***	0.003	-0.035***	-0.004	0.009	0.008	0.005	0.017
Single female household	0.009	-0.015	0.005	-0.088	0.064***	-0.011	0.034***	-0.068
Married household	0.013***	-0.010	0.007***	-0.051	0.020***	-0.006	0.011***	-0.033
Children in family	-0.061***	-0.008	-0.036***	-0.038	-0.027***	-0.002	-0.015***	-0.010
Immigrant	-0.050***	-0.004	-0.029***	-0.026	-0.038***	-0.002	-0.020***	-0.014
Financially literate	0.025***	0.010	0.015***	0.056	0.035***	0.008	0.019***	0.046
Family financially literate	0.027***	-0.006	0.016***	-0.023	0.025***	-0.007	0.013***	-0.028
No education data	-0.079***	-0.013	-0.046***	-0.057	-0.125***	-0.028	-0.067***	-0.123
Getting married	0.098***	0.005	0.058***	0.028	0.088***	0.004	0.047***	0.021
Change to health	0.000	0.008	0.000	0.044	-0.007	0.004	-0.004	0.028
Having children	0.089***	0.015	0.053***	0.086	0.065***	0.010	0.035***	0.061
Region of Northern Jutland	0.057***	-0.010	0.034***	-0.040	0.061***	-0.012	0.032***	-0.046
Region of Middle Jutland	0.072***	-0.009	0.043***	-0.035	0.072***	-0.008	0.039***	-0.028
Region of Southern Denmark	0.047***	0.004	0.028***	0.038	0.049***	0.006	0.027***	0.046
Region of Zealand	-0.003	-0.013	-0.002	-0.063	-0.001	-0.010	-0.001	-0.046
Demeaned rank of:								
Age	-0.356***	0.043	-0.209***	0.210	-0.266***	0.049	-0.143***	0.231
Length of education	0.053***	-0.034	0.031***	-0.167	0.050***	-0.029	0.027***	-0.149
Income	-0.044***	-0.049	-0.026***	-0.263	0.064***	-0.056	0.034***	-0.294
Financial wealth	-0.322***	-0.061	-0.190***	-0.305	-0.321***	-0.051	-0.172***	-0.245
Housing wealth	0.186***	-0.002	0.109***	-0.002	0.181***	-0.018	0.097***	-0.077
non-linear transformation f(x), x is the demeaned rank of:								
Age					0.318***	0.042	0.171***	0.163
Length of education					-0.141***	-0.049	-0.076***	-0.220
Income					-0.163***	0.033	-0.088***	0.156
Financial wealth					0.018	0.084	0.010	0.442
Housing wealth					0.002	0.053	0.001	0.235
Intercept	-1.932***		-1.059***		-1.979***		-1.077***	
Coefficient of Proportionality	0.589***				0.536***			
Chi^2	1300.34				1588.26			
Likelihood ratio test p-value	0.000				0.000			

Figure 1: The history of 30-year Danish mortgage rates from 2003 to 2013

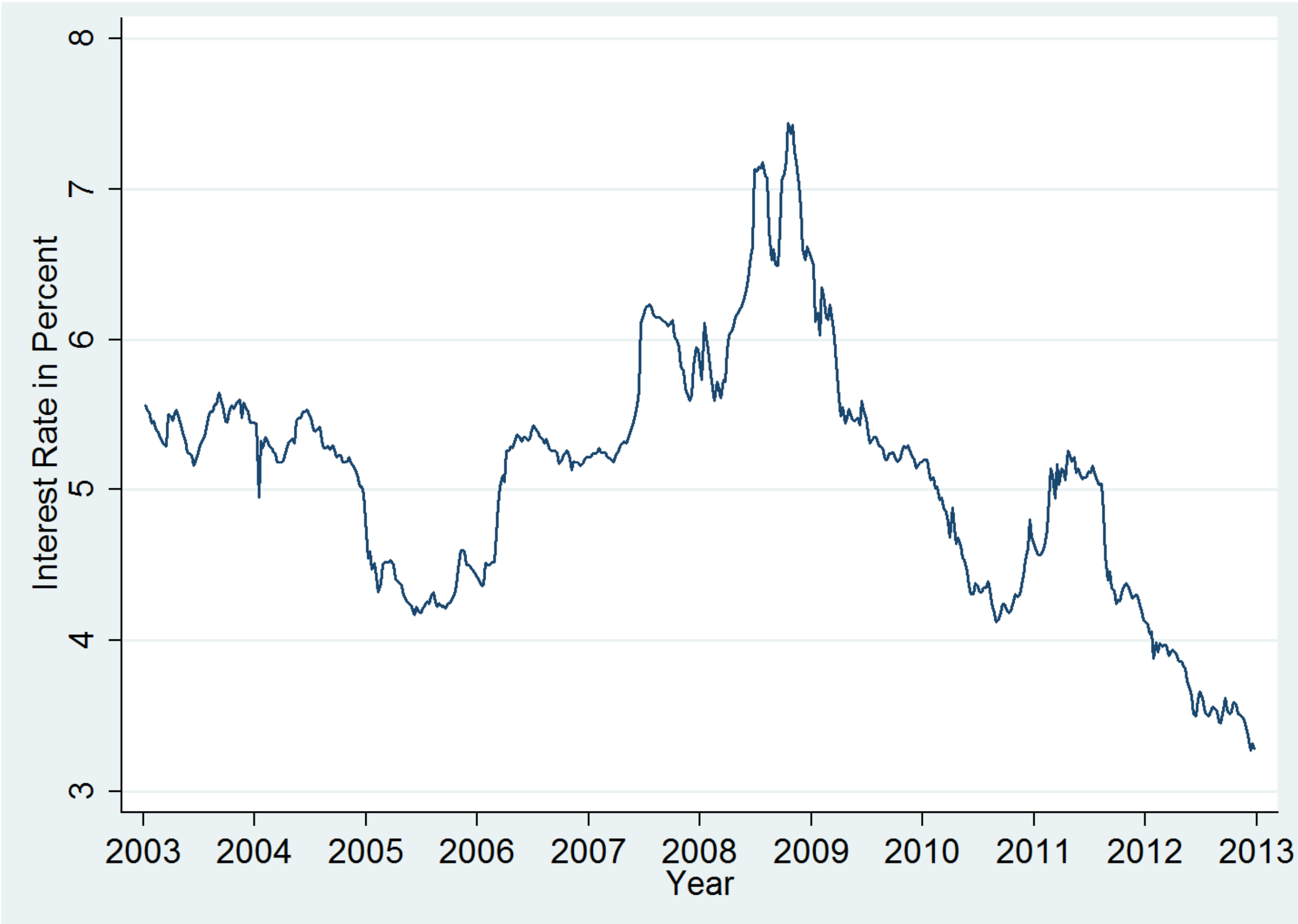


Figure 2: Histogram of estimated mortgage termination probabilities.

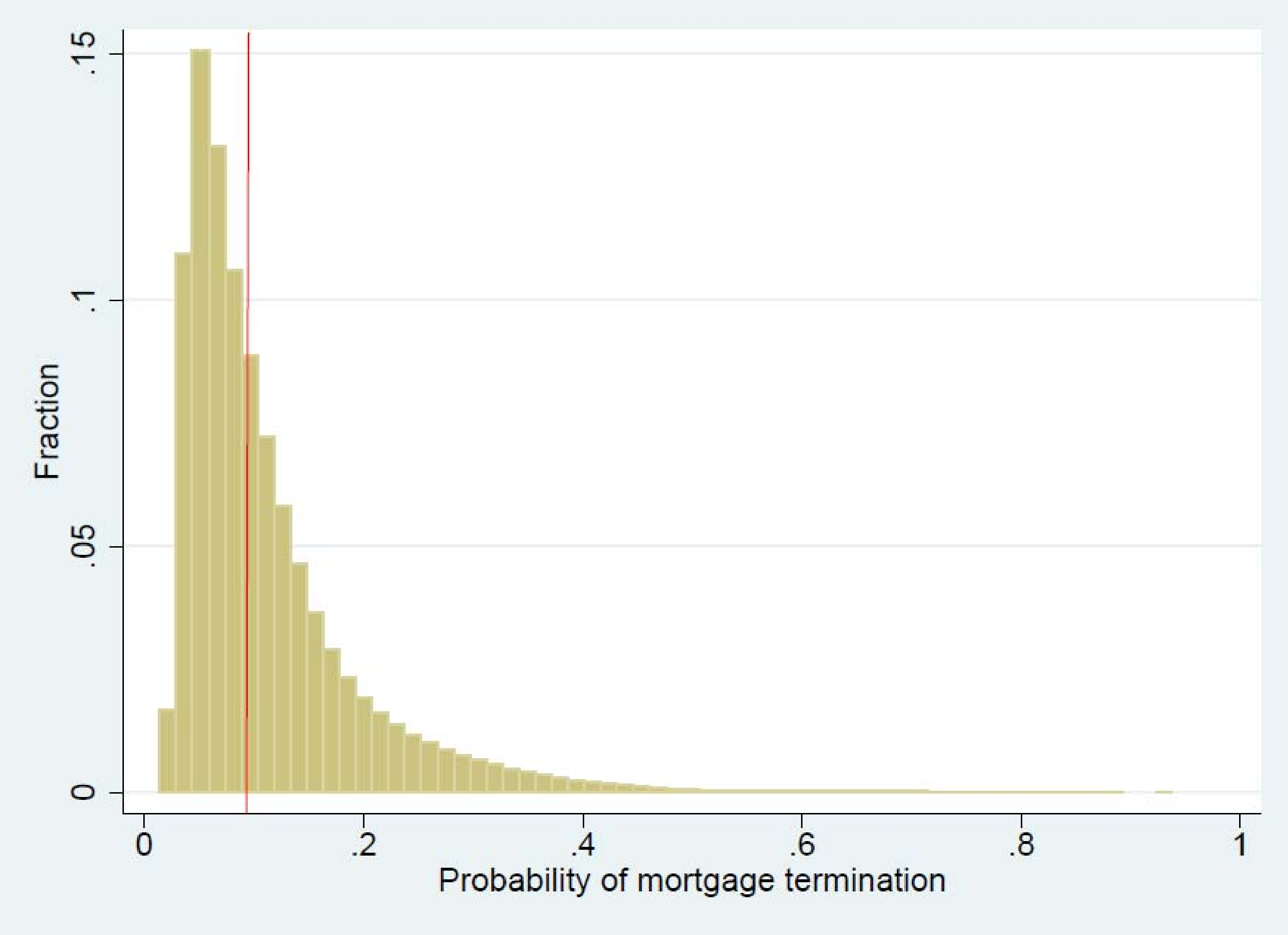
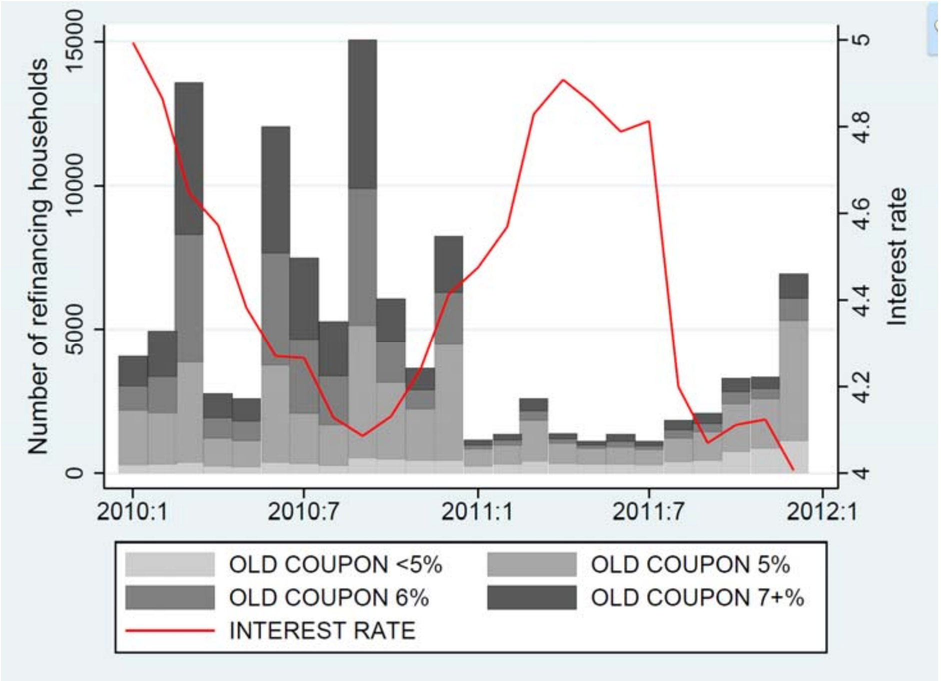


Figure 3: Refinancing activity by size of old and new mortgage coupon payments



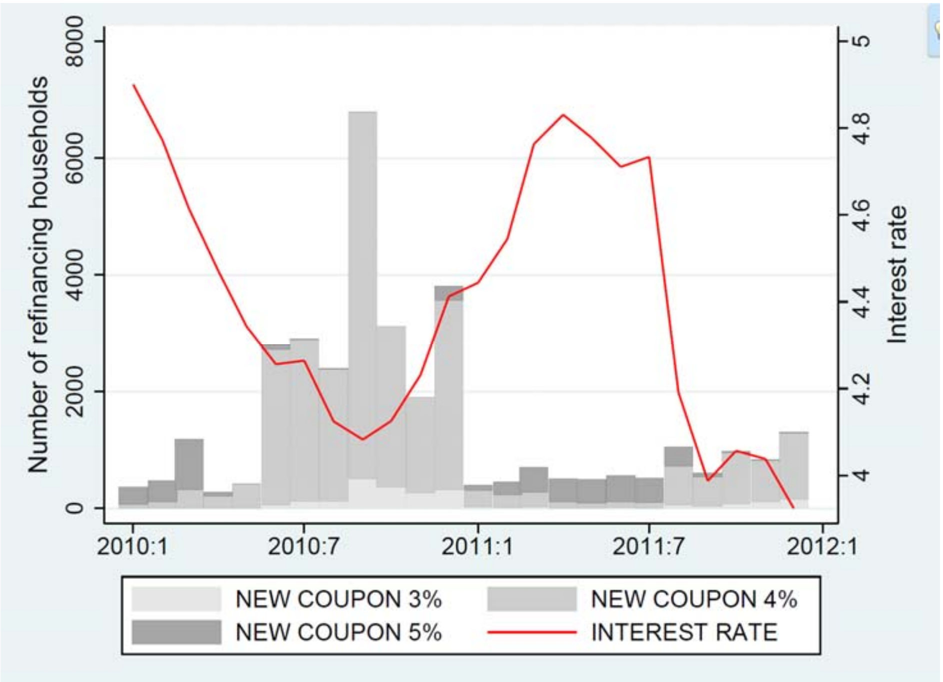


Figure 4: Effects of Age, Length of Education, Income, Financial Wealth, and Housing Wealth on Refinancing Probability

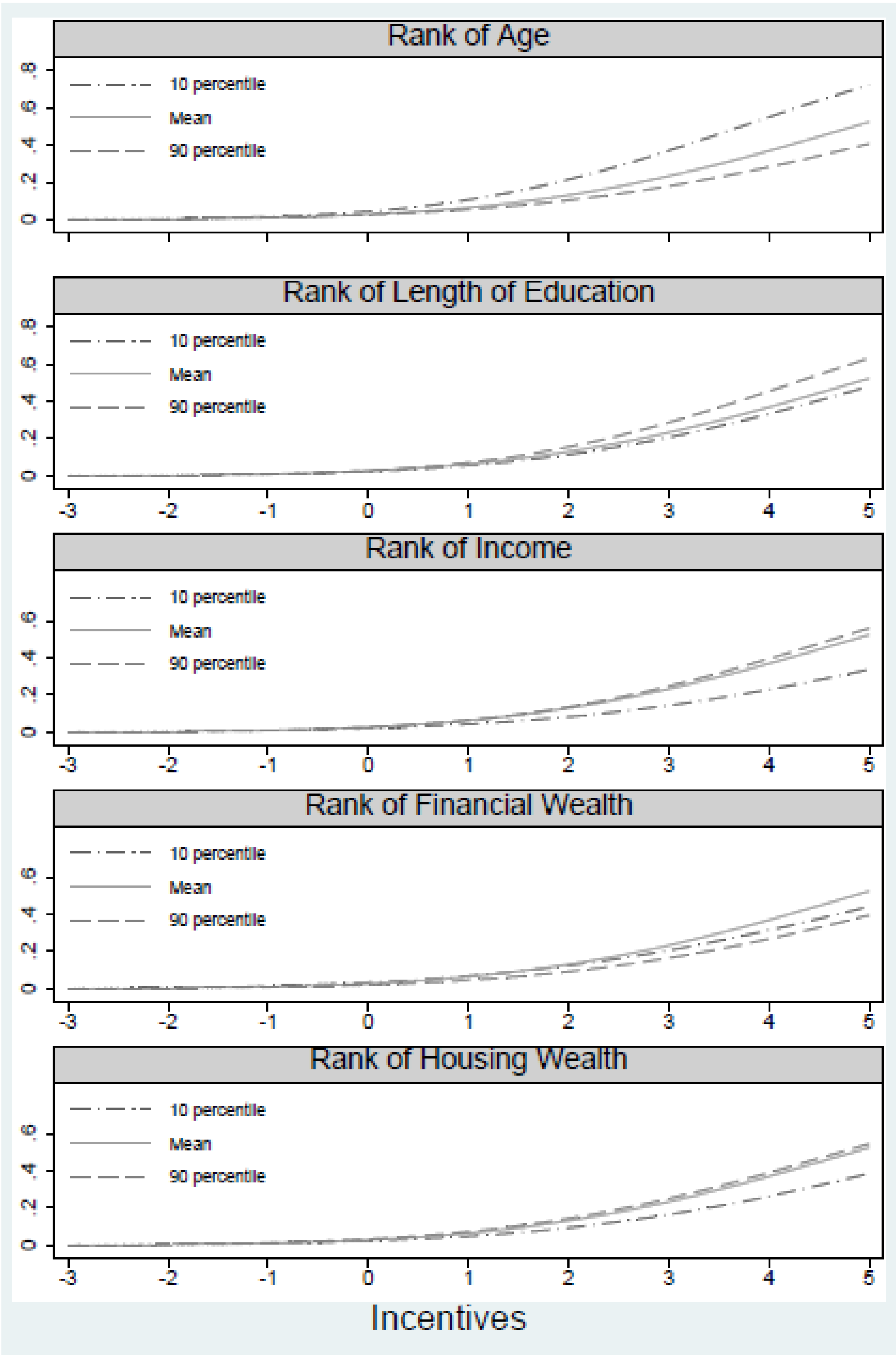


Figure 5: Proportionality of Inattention and Inertia