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Financial Mistakes Over the Life Cycle

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Abstract

We show that in ten different contexts –three kinds of credit card fee payments, credit card interest payments, interest rates on credit cards, mortgages, auto loans, home equity loans and credit lines, and small business credit cards– the young and the old pay more fees and face higher interest rates than the middle-aged. These results are not explained by commonly observed risk characteristics. We hypothesize that this may be a consequence of the interaction between experience and cognitive decline. The young have high cognitive skills, but little experience. The old have susbtantial experience, but declining cognitive skills. Although each individual case studied does not definitively establish either this hypothesis or even the u-shaped pattern of financial mistakes, the prevalence of this pattern in all ten contexts suggests there is a genuine underlying phenomenon.

JEL classification: D1, D4, D8, G2, J14.

Keywords: aging, auto loans, credit cards, fees, home equity, mortgages, shrouding.

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1 Introduction

Over their lifetimes, people face many choices about using complicated financial instruments. Mortgage and home equity loans come in multiple varities, each with different costs and benefits, and potential borrowers may have to search across mutliple lenders to obtain the best deal. Credit card fee structures may not be readily apparent. We might expect that not everyone will make the best choices; some will pay fees more often than others, or pay higher interest rates.

In this paper, we show that there are systematic differences over the life cycle in peoples' use of financial instruments. We find that the young–those in their twenties–and the old–those over 70–pay fees more frequently and pay higher interest rates than those aged in between. This u-shaped pattern of financial mistakes is present in the payment of three kinds of credit card fees; in overpayment of interest on balance transfer credit card offers; and in interest rates on home equity loans, home equity credit lines, credit cards, mortgage loans, auto loans, and small business credit cards. In each of these ten examples (from six separate data sets), we establish that the u-shape is present even conditioning on measures of risk or certain other.

We offer one parsimonious explanation for this persisent u-shape of financial mistakes. We hypothesize that peoples' 'financial savviness' depends on a combination of experience and cognitive ability. The young have little experience, but undiminished cognitive skills; the lack of experience makes them more prone to making mistakes. Over time, these consumers gain the experience that allows them to use both familiar and new products at lower cost. As consumers age, though, the marginal value of experience becomes smaller, while diminution of cognitive skills begins to erode some of the lessons they have learned earlier in life.

We note that none of the ten individual case studies we presents below definitively establishes this hypothesis, or even that there is a pattern by age. However, the fact that this u-shaped pattern emerged in all ten cases we considered shifted our prior beliefs that there is an important and unexplained phenomenon underlying financial changes by age.

The paper has the following organization. Section 2 described the basis structure to the empirical sections.. Section 3 describes the data and presents results on three kinds of credit card feel payments.. Section 4 describes the data and presents evidence on the use of balance transfer credit card offers. Section 5 describes the data and presents evidence on interest rates (APRs) on six different financial products. Section 6 presents a literature review. Section 7 concludes.

2 Overview

We document a u-shaped curve in financial "mistakes" over the lifecycle in ten separate contexts: credit card late payment fees; credit card over limit fees; credit card cash advance fees; use of credit card balance transfer offers; home equity loans; home equity lines of credit; auto loans; credit card interest rates; mortgages; and small business credit cards.

The mistakes come in three forms: higher fee payments; misuse of balance transfer offers; and higher APRs(interest rates)

For each context, there may be explanations other than mistakes for the patterns of fee payments or APRs by age; for example, higher APRs may reflect higher degrees of riskiness, which happen to be correlated with age. Thus, unless otherwise noted, in each context we estimate

$$F = \alpha + \beta Spline(Age) + \gamma Controls + \epsilon,$$

where F is the frequency of fee payment or the level of the APR paid by the borrower, $Controls$ is a vector of control variables intended to capture alternative explanations in each context (for example, measures of credit risk), and $Spline(Age)$ is a piecewise linear function that takes consumer age as its argument (with knot points at ages 30, 40, 50, 60 and 70). We then plot the fitted values for the spline on age. We also use the fitted values of the spline to create measures of the mistake amounts between ages 70 and 50, and between ages 50 and 20. Regressions are either pooled panel or cross-sectional, depending on the context.

Each section discusses the nature of the mistake, briefly documents the datasets used, and presents the regression results and graphs by age. We provide summary statistics for the data sets in an appendix.

3 Credit Card Fee Payments

3.1 Overview

Certain credit card uses involve the payment of a fee. Some kinds of fees are assessed when terms of the credit card agreement are violated. Other kinds are assessed for use of services.

We focus on three important types of fees: late fees, over limit fees, and cash advance fees.[1]

[1] Other types of fees include annual, balance transfer, foreign transactions, and pay by phone. All of these fees are relatively less important to both the bank and the borrower. Few issuers (the most notable exception being

We describe the fee structure for our data set below.

1. **Late Fee**: A late fee of between \$30 and \$35 is assessed if the borrower makes a payment beyond the due date on the credit card statement. If the borrower is late by more than 60 days once, or by more than 30 days twice within a year, the bank may also impose 'penalty pricing' by raising the APR to over 24 percent. The bank may also choose to report late payment to credit bureaus, adversely affecting consumers' FICO scores. If the borrower does not make a late payment during the six months after the last late payment, the APR will revert to its normal (though not promotional) level.

2. **Over Limit Fee**: An over limit fee, also of between \$30 and \$35, is assessed the first time the borrower exceeds his or her credit limit. The same penalty pricing as in the late fee is imposed.

3. **Cash Advance Fee**: A cash advance fee of the greater of 3 percent of the amount advanced, or \$5, is levied for each cash advance on the credit card. Unlike the first two fees, this fee can be assessed many times per month. It does not cause the imposition of penalty pricing on purchases or debt. However, the APR on cash advances is typically greater than that on purchases, and is usually 16 percent or more.

Payment of these fees may be viewed as mistakes in that fee payment may be avoided by small and relatively costless changes in behavior.

3.2 Data summary

We use a proprietary panel dataset from a large U.S. bank that issues credit cards nationally. The dataset contains a representative random sample of about 128,000 credit card accounts followed monthly over a 36 month period (from January 2002 through December 2004). The bulk of the data consists of the main billing information listed on each account's monthly statement, including total payment, spending, credit limit, balance, debt, purchases and cash advance annual percent rates (APRs), and fees paid. At a quarterly frequency, we observe each customer's credit bureau rating (FICO) and a proprietary (internal) credit 'behavior' score. We have credit bureau data

American Express) continue to charge annual fees, largely as a result of increased competition for new borrowers (Agarwal et al., 2005). The cards in our data do not have annual fees. We study balance transfer behavior using a separate data set below. The foreign transaction fees and pay by phone fees together comprise less than three percent of the total fees collected by banks.

about the number of other credit cards held by the account holder, total credit card balances, and mortgage balances. We have data on the age, gender and income of the account holder, collected at the time of account opening. Further details on the data, including summary statistics and variable definitions, are available in the data appendix.

3.3 Results

Table 1 presents panel regressions for each type of fee. In each of the three regressions, we regress a dummy variable equal to one if a fee is paid that month on a spline for age and control variables; hence the coefficients give the conditional effects of the independent variables on the propensity to pay fees. The controls include variables that might affect the propensity to pay fees. "Bill Existence Dummy$_{t-1}$" is a dummy variable equal to one if a bill was issued last month; borrowers will only be eligible to pay a late fee if a bill was issued. "Bill Activity Dummy" is a dummy variable equal to one if purchases or payments were made on the card; borrowers will only be eligible to pay over limit or cash advance fees if the card was used. "Purchases" is the amount purchased on the card, in dollars; we would expect that the propensity to pay over limit and cash advance fees would be increasing with the amount of purchases. "FICO" is the credit risk score, and "Behavior" is an internal risk score created by the bank to predict late and delinquent payment beyond that predicted by the FICO score. Higher scores mean less risky behavior. The scores are lagged three months because they are only updated quarterly. We would expect the underlying behavior leading to lower credit risk scores would lead to higher fee payment. "Debt/Limit" is the ratio of the balance of credit card debt to the credit limit; we would expect that having less available credit would raise the propensity to pay over limit fees, and possibly other fees.

All control variables have the expected signs and are statistically significant. Note that some control variables may partly capture the effects of age-related cognitive decline on fees. For example, if increasing age makes borrowers more likely to forget to pay fees on time, that would both increase the propensity to pay late fees and decrease credit and behavior scores. Hence the estimated coefficients on the age splines may understate some age-related effects.

Coefficients on the age splines are uniformly negative for splines through age 50, negative or weakly positive for the spline between age 50 and 60, and positive with increasing slope for splines above age 50.

Figures 1 through 3 plot fitted values for the age splines for the three kinds of fees. All three show the pronounced u-shape in the propensity of fee payment implied by the regression results.

Fee payment declines sharply between ages 18 and 30, remains about flat through the late 60s, and rises sharply at higher ages.

To gain a measure of the size and statistical significance of the effects, we compute the difference between the fitted values at age 70 and 50, and the difference between the fitted value at age 50 and 20 for each of the three kinds of fees, reported in the table below.

	Differences in Fee Payment Frequency by Age and Fee Type		
	Late Fee	Over Limit Fee	Cash Advance Fee
Fees Paid at Age 70 - Fees Paid at Age 50	0.0054	0.0012	0.0010
	(0.0017)	(0.0005)	(0.0003)
Fees Paid at Age 50 - Fees Paid at Age 20	0.0177	0.0116	0.0187
	(0.0007)	(0.005)	(0.0056)

The differences are statistically significant in all cases. They are more economically significant for the younger age comparison, though part of that is attributable to the choice of age 70.

4 'Eureka' Moments: Balance Transfer Credit Card Usage

4.1 Overview

Credit card holders frequently receive offers to transfer account balances on their current cards to a new card. Borrowers pay substantially lower APRs on the balances transferred to the new card for a six-to-nine-month period (a 'teaser' rate). However, new purchases on the new card have high APRs, and payments on the new card go first towards paying down the balance transferred, and only subsequently towards new purchases.

The optimal strategy for borrowers, then, is to make no new purchases on the card to which balances have been transferred. We hypothesize that some borrowers will figure this out before making any new purchases on the card. Some borrowers may not be initially informed about the card terms, and will only learn about them by observing interest charges on purchases. Those borrowers will make purchases for one or more months, then have a 'eureka' moment, in which they learn not to make purchases, and make no new purchases therafter. Some borrowers will not figure our the strategy before the end of the promotional period.

4.2 Data summary

We use a proprietary panel dataset from several large financial institutions, later acquired by a single financial institution, that made balance transfer offers nationally. The data set contains 14,798 accounts which accepted such offers over the period January 2000 through December 2002, The bulk of the data consists of the main billing information listed on each account's monthly statement, including total payment, spending, credit limit, balance, debt, purchases and cash advance annual percent rates (APRs), and fees paid. We also observe the amount of the balance transfer, the start date of the balance transfer teaser rate offer, the initial teaser APR on the balance trasnder, and the end date of the balance transfer APR offer. At a quarterly frequency, we observe each customer's credit bureau rating (FICO) and a proprietary (internal) credit 'behavior' score. We have credit bureau data about the number of other credit cards held by the account holder, total credit card balances, and mortgage balances. We have data on the age, gender and income of the account holder, collected at the time of account opening. Further details on the data, including summary statistics and variable definitions, are available in the data appendix.

4.3 Results

About one third of all balance transferers do no spending on the new card, thus figuring out the new strategy immediately. Slightly more than one third spend every month during the promotional period, thus never experiencing a "Eureka" moment.

Table 2 reports the results of regressing the month in which the borrower experiences a "Eureka" moment on a spline for age and controls. "FICO," measuring credit risk, is included because higher scores may be associated with greater financial savviness, which should lead borrowers to experience a Eureka moment sooner. Similarly, we would expect borrowers with higher levels of education to experience Eureka moments earlier. We also include gener and income.

The coefficients on the age spline show Eureka moments occurinng earlier through age 64, and later thereafter. Figure 4 plots, for each month in which the "Eureka" moment is experienced, the fraction of borrowers by age. The plot of those who never experience a "Eureka" moment–that is, who never figure out the strategy–is a very pronounced u-shape by age. The plot of those who figure out the strategy before making any purchases is a pronounced inverted u-shape. Plots for the other months are relatively flat.

5 APR Choice

Our remaining six examples are over interest rates paid on different types of borrowing: home equity loans and credit lines; credit cards; mortgages; auto loans; and small business credit cards. In each case, we will show that, after controlling for measures of credit risk and other variables, both the young and the old consistently pay higher APRs than those in between.

5.1 Home Equity Loans and Credit Lines

5.1.1 Data Summary

We use a proprietary panel dataset from a large financial institution that issued home equity loans and home equity lines of credit nationally. Between March and December 2002, the lender offered a menu of standardized contracts for home equity credits. Consumers could choose between a credit loan and line; between a first and second lien; and could choose to pledge different amounts of collateral (implying a loan-to-value (LTV) ratio of less than 80 percent, between 80 and 90 percent, and between 90 an 100 percent). In effect, the lender offered twelve different contract choices. For 75,000 such contracts, we observe the contract terms, borrower demographic information (age, years at current job, home tenure), financial information (income and debt-to-income ratio), and risk characteristics (credit (FICO) score, and LTV). We also observe borrower estimates of their house values and the loan amount requested.

5.1.2 Results

Table 3 reports the results of estimating regressions of APRs (interest rates) on home equity loans and lines of credit on a spline for age and control variables. The control variables are similar to those used in the credit card fee regressions, though here they are introduced for different reasons. The FICO, or credit risk, score is included because riskier borrowers should pay higher APRs, as should borrowers with a higher debt-to-income level. Borrowers with higher income should pay lower interest rates. Borrowers with higher LTVs should pay higher interest rates, particularly given the structure of loan offerings.

We again find that all control variables have the expected sign and are statistically significant. For both loans and credit lines, we find that APR declines by age through age 50, and rises thereafter.

Figure 5 plots the fitted values on the spline for age for home equity lines and loans. Both show a pronounced u-shape, with younger and older borrowers paying more than 100 basis points more than borrowers in their late forties. In the table below, we again compute the difference between APRs paid at age 70 and age 50, and the difference in APRs paid at age 50 and age 20. The differences are statistically significant, and highly economically significant.

	Differences in APR by Age	
	Home Equity Loan	Home Equity Credit Line
APR Paid at Age 70 - APR Paid at Age 50	0.3853	0.4645
	(0.1959)	(0.1001)
APR Paid at Age 50 - APR Paid at Age 20	0.7735	0.7181
	(0.2476)	(0.0899)

5.1.3 One Mechanism: Borrower Misestimation of Home Values

The amount of collateral offered by the borrower, as measured by the loan-to-value (LTV) ratio, is an important determinant of loan APRs. Higher LTVs imply higher APRs, since the fraction of collateral is lower. At this financial institution, borrowers estimate their home values, and ask for a credit loan or line falling into one of three categories depending on the implied LTV. The financial institution separately verifies the house value.

If the borrower has overestimated the value of the house, so that the LTV is in fact higher than originally estimated, the financial institution will direct the buyer to a different loan with a higher interest rate corresponding to the higher LTV. If the borrower has underestimated the value of the house, however, the financial institution need not direct the buyer to a loan with a lower interest rate corresponding to the actual lower LTV; it may simply choose to offer the same, higher interest rate, for a lower-risk loan.

We therefore predict that buyers who underestimate their home values pay higher APRs than those who accurately estimate them, while those who overestimate their home values pay about the same APRs. If this is true, and if underestimation is U-shaped with age, then underestimation would provide a mechanism through which age affected the APR paid. In equilibrium, the underestimators will subsidize those who either accurately estimate or who overestimate.

Pence (2006) presents evidence that borrowers do not generally acturately know the values of their houses.

Figure 6 plots the percent underestimation and overestimation of house value by age. The chart shows U-shapes for both, more pronouncedly so for under-estimation, with the young and the elderly underestimating by more than double the percentage than those at age 50.

Figure 7 plots the fitted values from re-estimating the regressions in table 3 while including a variable equal to zero if the borrower overestimates, and by the percent underestimation if the borrower underestimates (regression not reported). The U-shape is much less pronounced in this chart than in the comparable chart without this variable, suggesting that the age-related phenomenon of underestimation is driving the age effect. We also separately verified that, conditioning on actual LTV, borrowers who overestimate do not pay higher APRs on average.

5.2 Credit Cards

5.2.1 Data Summary

We use the same dataset as for the fee payment results described above.

5.2.2 Results

Table 4 reports the results of regressing credit card APRs on a spline with age as the argument and other control variables. We again expect APRs to decline with better credit (FICO) scores. APRs should rise with "Total Number of Cards" and "Total Card Balance," fall with "Log(Income),“ and rise with "Home Equity Loan Balance" and "Mortgage Loan Balance," since those variables may contribute to risk of default in ways observable to the bank but not fully captured by FICO score.

The control variables generally have the expected sign, though, aside from the FICO score, they are generally not statistically significant–perhaps suggesting that the FICO score may well be capturing the impact of the other control variables on defauly risk. The coefficients on age are negative through age 50, and positive thereafter. The magnitudes of the coefficients are quite small, though, and the individual splaines are not statistically significant.

Figure 8 plots the fitted values on the spline for age. A u-shape is present, though much less pronounced than in the case of home equity loans. The table below again presents the difference between the APR paid at age 70 and that paid at age 50, and the difference between the APR paid at age 50 and that paid at age 20. The differences are positive, though small and not statistically significant.

	Differences in APR by Age
APR Paid at Age 70 - APR Paid at Age 50	0.0390
	(0.0573)
APR Paid at Age 50 - APR Paid at Age 20	0.1797
	(0.1334)

5.3 Auto Loans

5.3.1 Data Summary

We use a proprietary data set of auto loans originated at several large financial institutions that were later acquired by another institution. The data set comprises observations on 6996 loans originated for the purchase of new and used automobiles. We observe loan characteristics inclduing the automobile value and age, the loan amount and LTV, the monthly payment, the contract rate, and the time of origination. We also observe borrower characteristics including credit score, monthly disposable income, and borrower age.

5.3.2 Results

Table 5 reports the results of estimating a regression of the APR paid on auto loans on a spline with age as the argument and control variables. For the same reasons as given in other cases above, we expect APRs to fall with higher credit scores and incomes and rise with the debt-to-income ratio. We also include car characteristics, such as type and age, as one of us has found those variables to matter for APRs in other work (Agarwal, Ambrose and Chomsisengphet, forthcoming)–though we note that the financial institutions do not condition their loans on such variables. We also include loan age and state dummies, though we do not report the latter to save space.

We again find the control variables to have the expected sign and be statistically significant. Age lowers the APR through age 50, and raises it thereafter.

Figure 9 plots the fitted values on the spline for age. The graph again shows a rather pronounced u-shape. The table below provides APR differences between ages 70 and 50, and 50 and 20, respectively.

	Differences in APR by Age
APR Paid at Age 70 - APR Paid at Age 50	0.0845
	(0.0305)
APR Paid at Age 50 - APR Paid at Age 20	0.2310
	(0.0342)

5.3.3 Indirect Loans

The results above are for loans directly made by financial institutions to borrowers without any intermediaries–i.e. ones in which the borrower has directly approached the institutions. Many auto loans are made indirectly by banks and finance companies using the dealer as an intermediary. In a personal communication, Fiona Scott-Morton has informed us that, in the dataset used in Scott-Morton, XX, and YY, this u-shaped pattern unconditionally occurs for indirect loans.

5.4 Mortgages

5.4.1 Data Summary

We use a proprietary data set from a large financial institution that originates first mortgages in Argentina. The data set covers 4,867 owner-occupied, fixed rate, first mortgage loans originated between June 1998 and March 2000, and observed through March 2004. We observe the original loan amount, the LTV and appraised house value at origination, and the APR. We also observe borrower financial characteristics (including income, second income, years on the job, wealth measures such as second house ownership and car ownership and value), borrower risk characteristics (Veraz score (a credit score similar to the U.S. FICO score) and mortgage payments as a percentage of after-tax income), and borrower demographic characteristics (age, gender and marital status).

5.4.2 Results

Table 6 reports results of regressing the mortgage APR on a spline with age as an argument and control variables. As controls, we include risk measures (credit score, income, mortgage payment as a fraction of income, and LTV), and various demographic and financial indicators (gender, marital status, car ownership dummy, and several others; these coefficients are not reported to save space). The coefficients on the controls are again of the expected sign and generally statistically significant.

The coefficients on the age apline are positive below age thirty, then negative through age 60 and positive thereafter. Figure 10 plots the fitted values on the spline for age. The graph again generally shows a u-shape, though behavior for younger borrowers is rather different. The table below provides APR differences between ages 70 and 50, and 50 and 20, respectively.

	Differences in APR by Age
APR Paid at Age 70 - APR Paid at Age 50	0.0282
	(0.0457)
APR Paid at Age 50 - APR Paid at Age 20	0.0648
	(0.0587)

5.5 Small Business Credit Cards

5.5.1 Data Summary

We use a proprietary data set of small business credit card accounts originated at several large institutions that issued such cards nationally. The institutions were later acquired by a single institution. The panel data set covers 11,254 accounts originated between May 200 and May 2002. Most of the business are very small, owned by a single family, and have no formal financial records. The data set has all information collected at the time of account origination, including the borrower's self-reported personal income, years in business of the firm, and borrower age. Quarterly, we observe the account credit bureau score.

5.5.2 Results

Table 7 reports the results of regressing the APR for small business credit cards on a spline with age as the argument and control variables. As with individual credit card accounts, we control for the FICO score of hte borrower, the total number of cards, card balance, and card limit. We also include dummy variables for years in business (not reported to save space), and expect APRs to be decreasing in this variable. All controls variales are statistically significant and have the expected sign.

APRs are decreasing in the age of hte borrower through age 60, and increasing thereafter. Figure 11 plots the fitted values on the splane for age. The graph shows a pronounced u-shape. The table below provides APR differences between ages 70 and 50, and 50 and 20, respectively.

	Differences in APR by Age
APR Paid at Age 70 - APR Paid at Age 50	0.0432
	(0.0518)
APR Paid at Age 50 - APR Paid at Age 20	0.2629
	(0.0475)

5.6 Default Rates

Although all seven APR regressions show a u-shaped pattern by age, it remains possible that this is an artifact of improper control variables. In particular, the controls for default risk may be inadequate. If default is in fact generally u-shaped by age, then APRs should also be u-shaped by age.

We test this by regressing default rates on age splines for credit cards, auto loans, and home equity loans and credit lines. We plot fitted values in Figure 12. None of the graphs is u-shaped. On the contrary, home equity loans and lines show a pronounced inverted u-shape, implying that the young and old have lower default rates. Credit cards and auto loans also show a slight inverted u-shape. These results deepen the puzzle of the common u-shape.

6 Literature Review

[Aging]

[Financial mistakes/learning about financial issues]

[Aguiar and Hurst]

Our paper is related to several branches of the literature. A number of researchers have written about consumer credit card use. Our work most closely overlaps with that of Agarwal *et al.* (2005), who use another large random sample of credit card accounts to show that, on average, borrowers choose credit card contracts that minimize their total interest costs net of fees paid. About 40 percent of borrowers choose suboptimal contracts that result in their paying avoidable interest costs. While some borrowers incur hundreds of dollars of such costs, most of these borrowers subsequently switch to cost-minimizing contracts. The results of our paper complement those of Agarwal *et al.* (2005), since we find evidence of learning to avoid fees and interest costs given a particular card contract.

Several researchers have looked at the response of consumers to low, introductory credit card rates ('teaser' rates), and at the persistence of otherwise high interest rates. Ausubel (1999) uses a panel dataset to document adverse selection in the response of consumers to credit card solicitations. He finds evidence that consumers overreact to credit card teaser rates and argues that this may occur because they underestimate the chance that they will borrow when the teaser rates expires. Shui and Ausubel (2004) show that consumers prefer credit card contracts with low initial rates for a short period of time to ones with somewhat higher rates for a longer period of time, even when the latter is *ex post* more beneficial. Consumers also appear 'reluctant' to switch contracts. DellaVigna and Malmendier (2004) theorize that financial institutions set the terms of credit card contracts to reflect consumers' poor forecasting ability over their future consumption. Bertrand *et al.* (2005) find that randomized changes in the "psychological features" of consumer credit offers affect adoption rates as much as variations in the interest rate terms. Ausubel (1991) hypothesizes that consumers may be over-optimistic, repeatedly underestimating the probability that they will borrow, thus possibly explaining the stickiness of credit card interest rates. Calem and Mester (1995) use the 1989 Survey of Consumer Finances (SCF) to argue that information barriers create high switching costs for high-balance credit card customers, leading to persistence of credit card interest rates, and Calem, Gordy and Mester (2005) use the 1998 and 2001 SCFs to argue that such costs continue to be important. Kerr and Dunn (2002) use data from the 1998 SCF to argue that having large credit card balances raises consumers' propensity to search for lower credit card interest rates. Kerr (2004) use SCF data to argue that banks offer better lending terms to consumers who are also bank depositors, and about whom the bank would thus have more information.

Other authors have used credit card data to evaluate more general hypotheses about consumption. Agarwal, Liu and Souleles (2004) use credit card data to examine the response of consumers to the 2001 tax rebates. Gross and Souleles (2002a) use credit card data to argue that default rates rose in the mid-1990s due to declining default costs, rather than a deterioration in the creditworthiness of borrowers. Gross and Souleles (2002b) find that increases in credit limits and declines in interest rates lead to large increases in consumer debt. Ravina (2005) estimates consumption Euler equations for credit card holders and finds evidence for habit persistence.

7 Conclusion

We show that the young and the old pay higher fees and higher interest rates in ten separate contexts: three types of credit card fees, balance transfer interest payments, and interest rates on home equity loans, home equity lines of credits, mortgages, auto loans, credit cards, and small business credit cards. This u-shaped patern of financial mistakes exists even controlling for common measures of risk, such as FICO scores, on which loans are priced.

The presence of a common pattern by age might immediately suggest the presence of age discrimination. We believe this to be highly unlikely, for two reasons. First, firms explicitly seek to avoid discrimination by age, to avoid lawsuits. Penalties for age discrimination from the Fair Lending Act are quite substantial (as would be the resulting negative publicity), making the cost of such discrimination very high. Second, the u-shaped pattern shows up in contexts such as fee payments and misuse of balance transfer offers in which discrimination is not feasible (since all cardholders face the same rules).

Higher interest rates might also be a consequence of higher default rates. Though this explanation would again not apply in the case of credit card fee payments or misuse of balance transfers, we again think it is unlikely in cases in which it is applicable because default rates seem to have an inverted u-shape by age–that is, the young and the old seem to be lower risks for default.

A parsimonious explanation that accounts for all of these cases is one in which 'financial savviness' depends on both experience and cognitive skill. Experience with financial products rises with age, though likely with diminishing marginal returns. Pyschology studies have shown that cognitive skills decline starting in one's early twenties. The young have unimpaired cognitive skills, but little experience, and thus do not choose wisely. Those in their thirties through sixties have increasing experience and relatively undiminished cognitive skills. By age 70, the effects of declining cognitive skills start to strongly attenuate the benefits of high experience.

Each of the cases described here does not per se compelling show that there is a u-shaped pattern of financial mistakes by age, or that such a pattern is due to the mechanism described above. But all ten cases together have moved our prior beliefs that there is some genuine underyling phenomenon that is deserving of further study.

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Appendix A: Data Summary Statistics

Table A1: Credit Cards

Description (Units)	Freq.	Mean	Std. Dev.
Account Characteristics			
Purchase APR	M	14.40	2.44
Interest Rate on Cash Advances (%)	M	16.16	2.22
Credit Limit ($)	M	8,205	3,385
Current Cash Advance ($)	M	148	648
Payment ($)	M	317	952
New Purchases ($)	M	303	531
Debt on Last Statement ($)	M	1,735	1,978
Minimum Payment Due ($)	M	35	52
Debt/Limit (%)	M	29	36
Fee Payment			
Total Fees ($)	M	10.10	14.82
Cash Advance Fee ($)	M	5.09	11.29
Late Payment Fee ($)	M	4.07	3.22
Over Limit Fee ($)	M	1.23	1.57
Extra Interest Payments:			
... Due to Over Limit or Late Fee ($)	M	15.58	23.66
... Due to Cash Advances ($)	M	3.25	3.92
Cash Advance Fee Payments/Month	M	0.38	0.28
Late Fee Payments/Month	M	0.14	0.21
Over Limit Fee Payments/Month	M	0.08	0.10
Borrower Characteristics			
FICO (Credit Bureau Risk) Score	Q	731	76
Behavior Score	Q	727	81
Number of Credit Cards	O	4.84	3.56
Number of Active Cards	O	2.69	2.34
Total Credit Card Balance ($)	O	15,110	13,043
Mortgage Balance ($)	O	47,968	84,617
Age (Years)	O	42.40	15.04
Income ($)	O	57,121	114,375

Notes: The "Credit Bureau Risk Score" is provided by Fair, Isaac and Company (hence 'FICO'). The greater the score, the less risky the consumer is. The "Payment Behavior Score" is a proprietary score based on the consumer's past payment history and debt burden, among other variables. It is created by the bank to capture determinants of consumer payment behavior not accounted for by the FICO score. "Q" indicates the variable is observed quarterly, "M" monthly, and "O" only at account origination.

Table A2: Home Equity Loans and Credit Lines

	Loans		Credit Lines	
Description (Units)	Mean	Std. Dev.	Mean	Std. Dev.
APR(%)	7.96	1.16	4.60	0.88
Borrower Age (Years)	43	14	46	12
Income ($, Annual)	78,791	99,761	90,293	215,057
Debt/Income (%)	40	18	41	19
FICO (Credit Bureau Risk) Score	713	55	733	49
Customer LTV (%)	66	26	62	24
Appraisal LTV (%)	69	29	64	23
Borrower Home Value Estimate ($)	196,467	144,085	346,065	250,355
Bank Home Value Estimate ($)	186,509	123,031	335,797	214,766
Loan Requested by Borrower ($)	43,981	35,161	61,347	50,025
Loan Approved by Bank ($)	42,871	33,188	60,725	51,230
First Mortgage Balance ($)	79,496	83,560	154,444	112,991
Months at Address	92	122	99	129
No First Mortgage (%)	29	45	15	42
Second Home (%)	3	14	3	12
Condo (%)	8	18	6	17
Refinancing (%)	66	47	39	49
Home Improvement (%)	18	39	25	44
Consumption (%)	16	39	35	35
Self Employed (%)	7.9	27	7.8	27
Retired (%)	9.5	29	7.7	27
Homemaker (%)	1.4	12	1.3	11
Years on the Last Job	6.3	8.1	7.6	9.1

Table A3: Mortgage Loans

	Loans	
Description (Units)	Mean	Std. Dev.
APR(%)	12.64	2.17
Borrower Age (Years)	40.54	9.98
Income ($)	2,624	2,102
Monthly Mortgage Payment/Income (%)	22.84	12.12
Veraz (Credit Bureau Risk) Score	686	253
LTV (%)	61	17
Loan Amount ($)	44,711	27,048
Years at Current Job	9.43	8.01
Second House (%)	15.54	5.18
Car Ownership (%)	73.56	44.11
Car Value ($)	5,664	13,959
Gender (Female=1)	30.96	46.24
Second Income (%)	20.44	40.33
Married (%)	71.32	45.23
Married with Two Incomes (%)	16.75	37.34
Self Employed (%)	13.87	34.57
Professional Employment (%)	15.78	36.46
Nonprofessional Employment (%)	52.78	49.93
Relationship with Bank (%)	10.40	30.52

Table A4: Auto Loan APRs

Description (Units)	Mean	Std. Dev.
APR(%)	8.99	0.90
Borrower Age (Years)	40	21
Income ($, Monthly)	3416	772
LTV(%)	44	10
FICO (Credit Bureau Risk) Score	723	64
Monthly Loan Payment ($)	229	95
Blue Book Car Value ($)	11,875	4,625
Loan Amount ($)	4172	1427
Car Age (Years)	2	1
Loan Age (Months)	12	8

Table A5: Small Business Credit Cards APRs

Description (Units)	Mean	Std. Dev.
APR(%)	13.03	5.36
Borrower Age (Years)	47.24	13.35
Line Amount ($)	9,623.95	6,057.66
Total Unsecured Debt	12,627.45	17,760.24
FICO (Credit Bureau Risk) Score	715.86	55.03
Mortgage Debt ($)	102,684.70	160,799.57

Table 1: Credit Card Fees

	Late Fee	Over Limit Fee	Cash Advance Fee
Intercept	0.29640**	0.18700*	0.34310**
	(0.04456)	(0.08020)	(0.06309)
Age<=30	-0.00213**	-0.00134*	-0.00257*
	(0.00040)	(0.0060)	(0.00110)
30<Age<=40	-0.00061*	-0.00031**	-0.00041*
	(0.00029)	(0.00012)	(0.00019)
40<Age<=50	-0.00010**	-0.00018**	-0.00018*
	(0.00003)	(0.0006)	(0.00009)
50<Age<=60	0.00015**	-0.00020**	-0.00025**
	(0.00004)	(0.00007)	(0.00005)
60<Age<=70	0.00039*	0.00032**	0.00035**
	(0.00015)	(0.00011)	(0.00010)
Age >70	0.00254	0.00220*	0.00270
	(0.00129)	(0.00111)	(0.00139)
Bill Existence Dummy$_{t-1}$	0.01530*	0.01038**	0.01439**
	(0.00764)	(0.00309)	(0.00408)
Bill Activity Dummy	0.00730*	0.00882**	0.00552**
	(0.00341)	(0.00300)	(0.00205)
Purchases	0.01808**	0.01127**	0.01794*
	(0.00061)	(0.00227)	(0.00794)
Behavior$_{t-3}$	-0.00168**	-0.00310**	-0.00750*
	(0.00061)	(0.00115)	(0.00363)
FICO$_{t-3}$	-0.00160*	-0.00120**	-0.00150**
	(0.00070)	(0.00027)	(0.00048)
Debt/Limit	0.00657*	0.00348**	0.00379**
	(0.00326)	(0.00134)	(0.00117)
Adjusted R-squared			
No. of Obs.	3.9 million	3.9 million	3.9 million

Notes: Each column represents the panel regression of a fee payment in a particular month on a spline with borrower age as its argument and other financial control variables (described in the main body of the text). All regressions include account- and time- fixed effects. * denotes statistical significance at a 95 percent confidence level, and ** denotes statistical significance at a 99 percent confidence level.

Table 2: Eureka Moments

	Month of Eureka Moment
Intercept	4.0955**
	(0.5969)
25<=Age<=34	-1.3598**
	(0.4017)
35<=Age<=44	-2.7895**
	(0.4200)
45<=Age<64	-1.2253**
	(0.3966)
Age>65	1.3029**
	(0.4250)
FICO	-0.0525**
	(0.0042)
Some High School	1.4389
	(0.9144)
High School Graduate	1.0696**
	(0.3014)
Some College	0.6398*
	(0.2957)
Associate Degree	-0.5273
	(0.3834)
Bachelor's Degree	-0.4194
	(0.2540)
Graduate Degree	-0.5442*
	(0.2604)
Gender (Female=1)	0.1901**
	(0.0411)
Income	$-2.5\ 10^{-7}$*
	($1.2\ 10^{-7}$)
Adjusted R-squared	0.0822
No. of Obs.	

Notes: Each column represents the panel regression of the month in which the borrower did no more spending on the balance transfer card on a spline with borrower age as its argument and other control variables. * denotes statistical significance at a 95 percent confidence level, and ** denotes statistical significance at a 99 percent confidence level.

Table 3: Home Equity Loan and Credit Line APRs

	Home Equity Loan APR	Home Equity Credit Line APR
Intercept	8.13199**	7.28272**
	(0.11782)	(0.06094)
Age<=30	-0.06000**	-0.05600**
	(0.00829)	(0.00553)
30<Age<=40	-0.03365**	-0.02516**
	(0.00466)	(0.00248)
40<Age<=50	-0.01370**	-0.01865**
	(0.01045)	(0.00246)
50<Age<=60	0.00015	0.01673**
	(0.00710)	(0.00360)
60<Age<=70	0.02808*	0.02975**
	(0.01190)	(0.00648)
Age >70	0.03417	0.03650*
	(0.03040)	(0.01550)
Log(FICO)	-0.00221**	-0.00118**
	(0.00008)	(0.00004)
Log(Income)	-0.06860**	-0.15969**
	(0.00800)	(0.00398)
Debt/Income	0.00367**	0.00475**
	(0.00026)	(0.00014)
80<LTV<90	0.90564**	0.67879**
	(0.01093)	(0.00542)
LTV>=90	2.36912**	2.37995**
	(0.01233)	(0.00822)
Adjusted R-squared	0.7624	0.6175
No. of Obs.	16,523	71,733

Notes: Each column represents the regression of the APR paid by the borrower on the home equity loan or credit line on a spline with age as its argument, financial control variables (described in the main body of the text), and other variables not reported for reasons of space (state dummies, a dummy for loans made for home improvements, a dummy for loans made for refinancing, a dummy for no first mortgage on the property, months at the address, years worked on the job, dummies for self-employment, retiree, or homemaker status, and a dummy if the property is a condo). * denotes statistical significance at a 95 percent confidence level, and ** denotes statistical significance at a 99 percent confidence level.

Table 4: Credit Card APR

	APR
Intercept	14.27430**
	(3.03349)
Age<=30	-0.01270
	(0.00649)
30<Age<=40	-0.00749
	(0.00454)
40<Age<=50	-0.00413
	(0.00454)
50<Age<=60	0.00226
	(0.00596)
60<Age<=70	0.00165
	(0.01835)
Age >70	0.00164
	(0.03644)
FICO	-0.01828**
	(0.00148)
Total Number of Cards	0.77783
	(0.74734)
Total Card Balance	0.00022
	(0.00025)
Log(Income)	-5.05579
	(3.80280)
Home Equity Loan Balance	0.00031*
	(0.00022)
Mortgage Loan Balance	-0.00001
	(0.00003)
Adjusted R-squared	
No. of Obs.	

Notes: Each column represents the regression of the APR paid by the borrower on the credit card on a spline with age as its argument, and financial control variables (described in the main body of the text). *

denotes statistical significance at a 95 percent confidence level, and ** denotes statistical significance at a 99 percent confidence level.

Table 5: Auto Loan APR

	APR
Intercept	9.51890** (1.51220)
Age<=30	-0.02730** (0.00518)
30<Age<=40	-0.00379* (0.00049)
40<Age<=50	-0.00566** (0.00059)
50<Age<=60	0.00471** (0.00087)
60<Age<=70	0.00378* (0.00172)
Age >70	0.01058 (0.00510)
Income	-0.00004** (0.00000)
FICO	-0.00113** (0.00006)
Debt/Income	0.02300** (0.00198)
Japanese Car Dummy	-0.06217* (0.02873)
European Car Dummy	-0.01453** (0.00418)
Car Age	0.12590** (0.00320)
Adjusted R-squared	0.0928
No. of Obs.	6,996

Notes: Each column represents the regression of the APR paid by the borrower on the auto loan on a spline with age as its argument, financial control variables (described in the main body of the text), and state and quarter of purchases dummies (not reported). * denotes statistical significance at a 95 percent confidence level, and ** denotes statistical significance at a 99 percent confidence level.

Table 6: Mortgage APR

	Late Fee
Intercept	12.4366**
	(4.9231)
Age<=30	0.00273
	(0.0046)
30<Age<=40	-0.0023
	(0.0037)
40<Age<=50	-0.0056
	(0.0045)
50<Age<=60	-0.0127
	(0.0093)
60<Age<=70	0.0155
	(0.0434)
Age >70	0.0234
	(0.0881)
Log(Credit Score)	-0.1240**
	(0.0217)
Log(Income)	-0.2843*
	(0.1303)
Mortgage Payment/Income	0.0859
	(0.2869)
LTV	0.1845**
	(0.0187)
Adjusted R-squared	
No. of Obs.	

Notes: Each column represents the regression of the APR paid by the borrower on the auto loan on a spline with age as its argument, financial control variables (described in the main body of the text), and other demographic control variables not reported for space reasons (length of the loan term, and length of the loan term, squared, years on the job, dummies for a second home, having two incomes, being married with two incomes, being employed as a professional, being employed as a merchant, having had a previous relationship with the bank, having a car, being female or being married). * denotes statistical significance at a 95 percent confidence level, and ** denotes statistical significance at a 99 percent confidence level.

Table 7: Small Business Credit Card APR

	APR
Intercept	16.06010**
	(0.60750)
Age<=30	-0.02949**
	(0.00812)
30<Age<=40	-0.00682
	(0.00404)
40<Age<=50	-0.00472
	(0.00380)
50<Age<=60	-0.00165
	(0.00546)
60<Age<=70	0.00597
	(0.02090)
Age >70	0.01921
	(0.03301)
FICO	-0.01509**
	(0.00080)
Total Number of Cards	0.13786**
	(0.01531)
Total Card Balance	0.00004**
	(0.00000)
Total Card Limit	-0.00003**
	(0.00000)
Adjusted R-squared	0.0933
No. of Obs.	11,254

Notes: Each column represents the regression of the APR paid by the borrower on the small business credit card on a spline with age as its argument, financial control variables (described in the main body of the text), and dummies for number of years in business (not reported for reasons of space) * denotes statistical significance at a 95 percent confidence level, and ** denotes statistical significance at a 99 percent confidence level.

Figure 1: Frequency of Late Fee Payment by Borrower Age

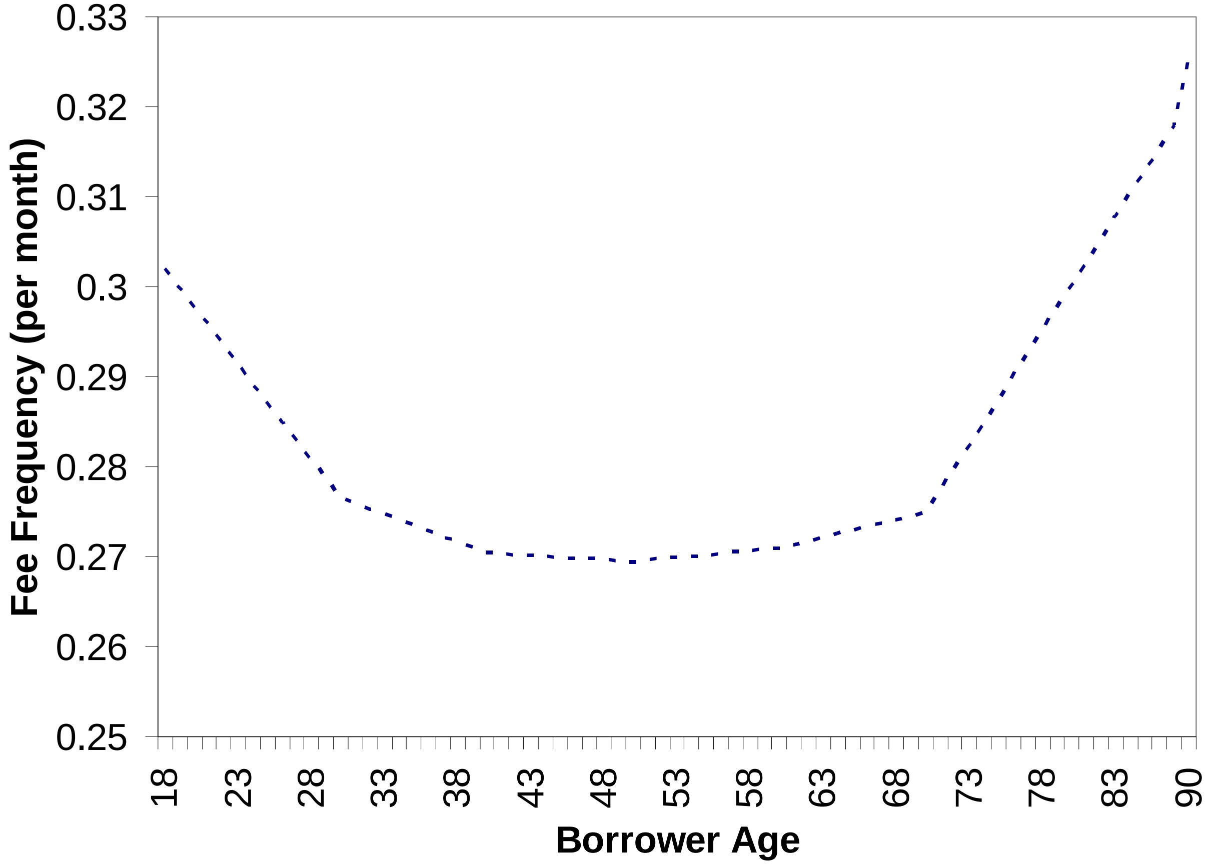


Figure 2: Frequency of Over Limit Fee Payment by Borrower Age

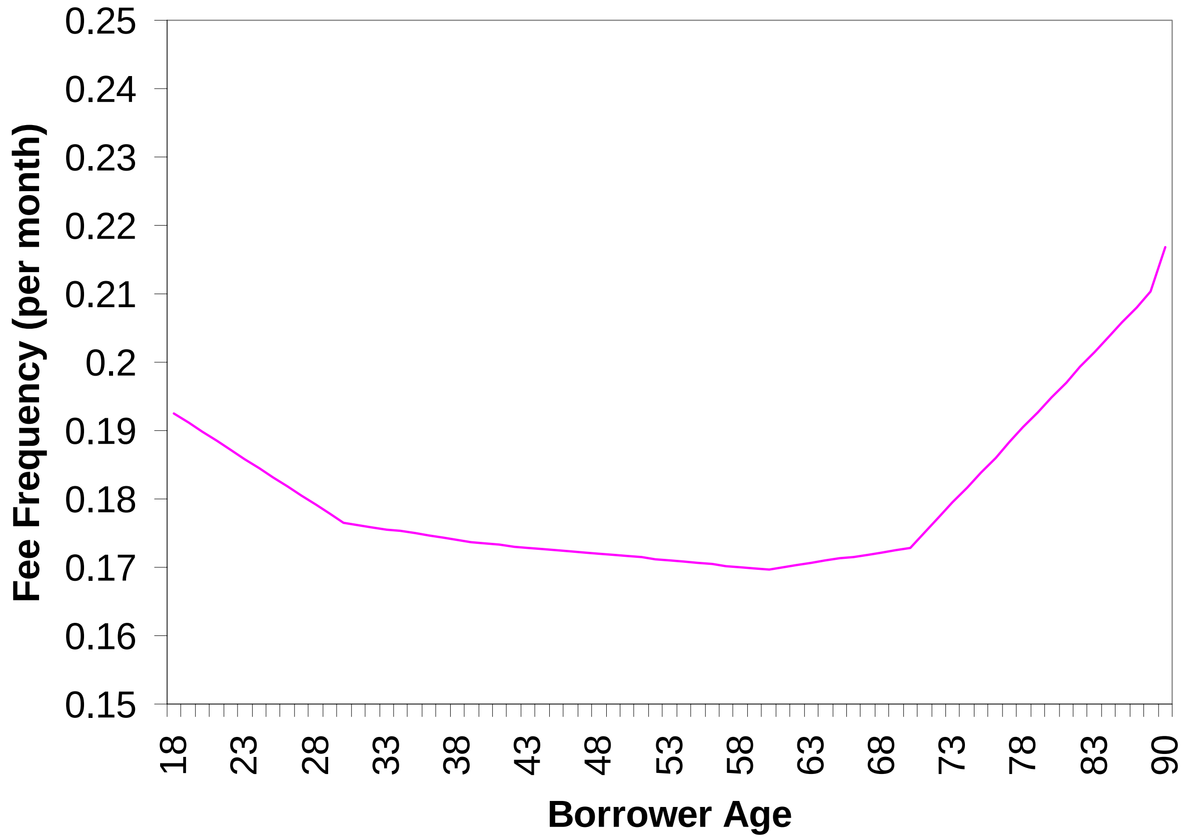
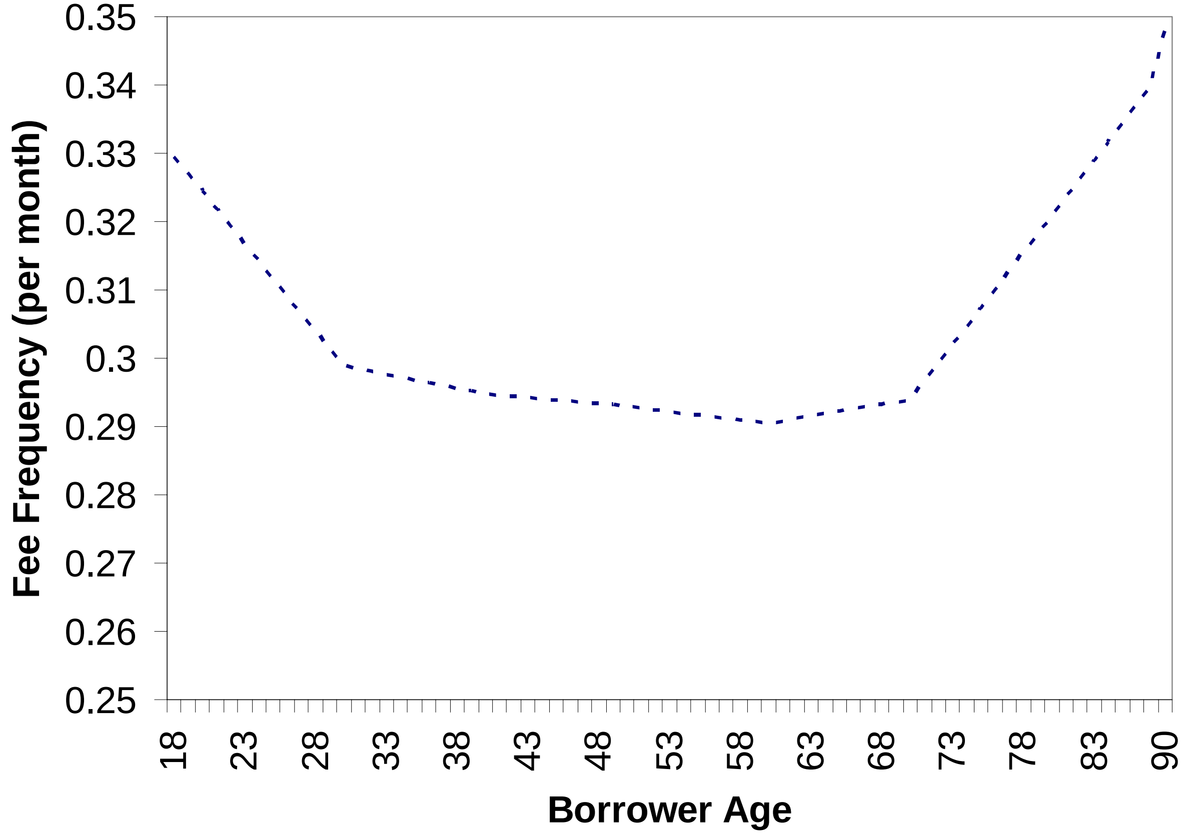


Figure 3: Frequency of Cash Advance Fee Payment by Borrower Age



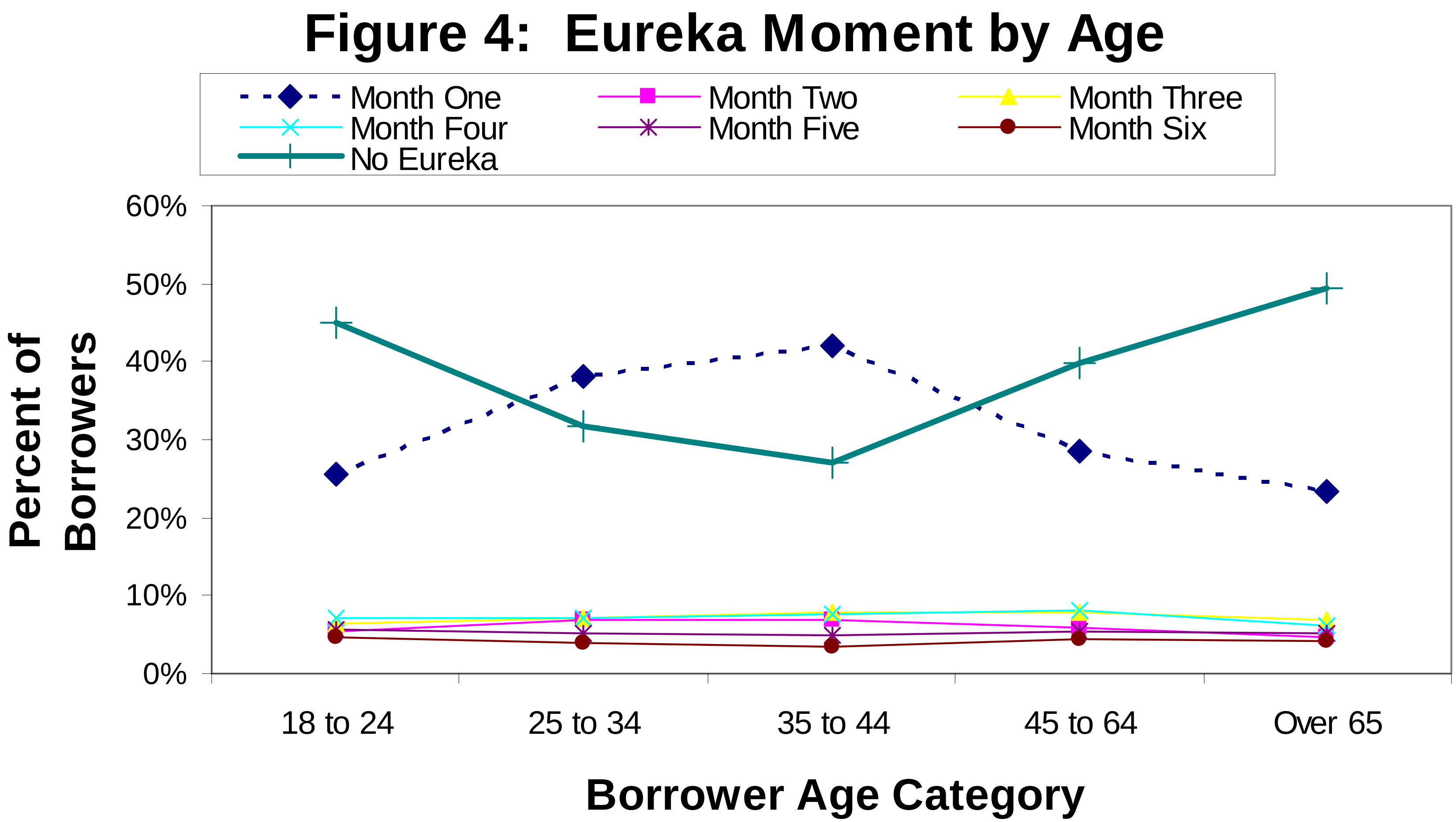


Figure 4: Eureka Moment by Age
Month One
Month Two
Month Three
Month Four
Month Five
Month Six
No Eureka
60%
50%
40%
30%
20%
10%
0%
Percent of Borrowers
18 to 24
25 to 34
35 to 44
45 to 64
Over 65
Borrower Age Category

Figure 5: Home Equity Loan and Credit Line APRs by Borrower Age

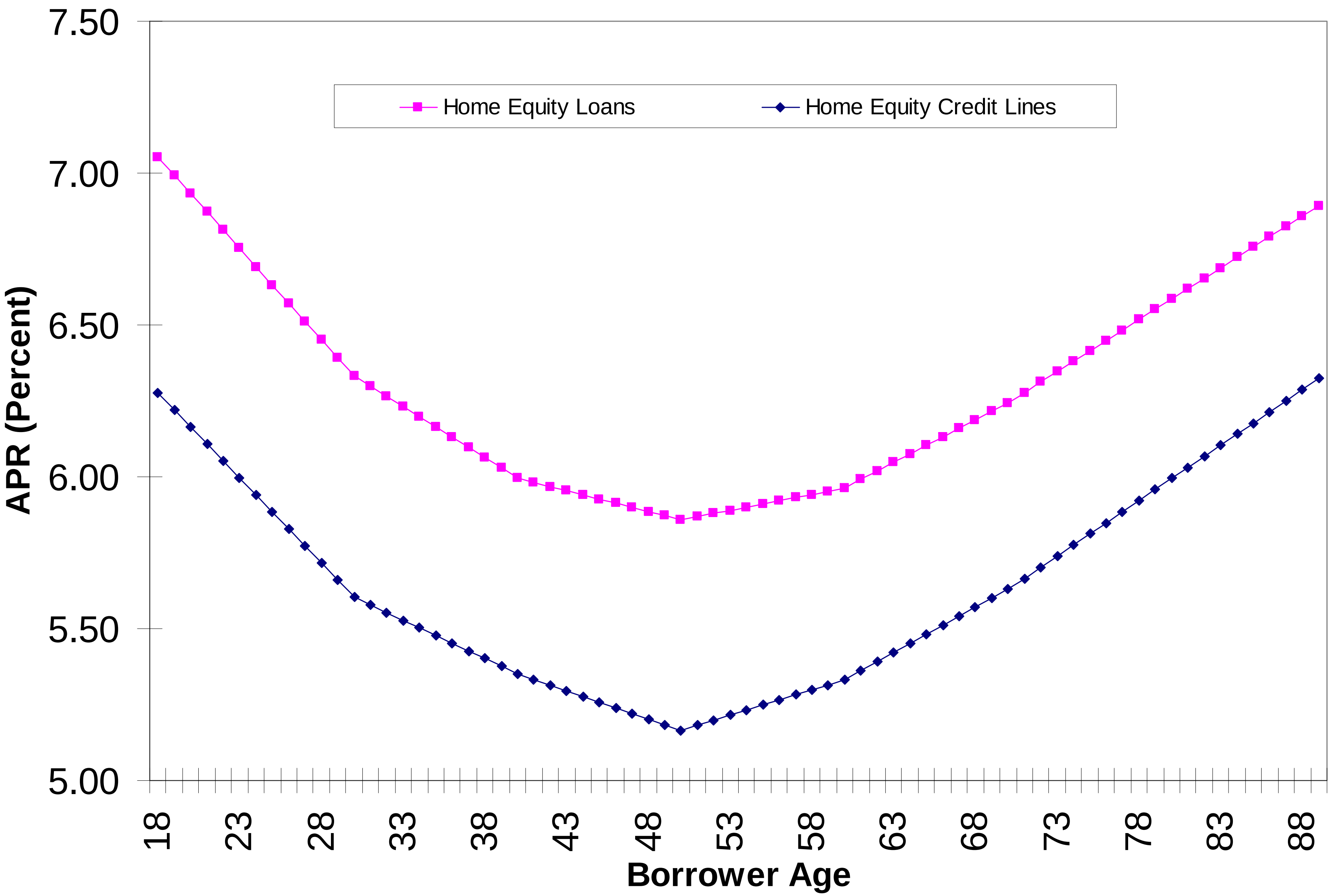
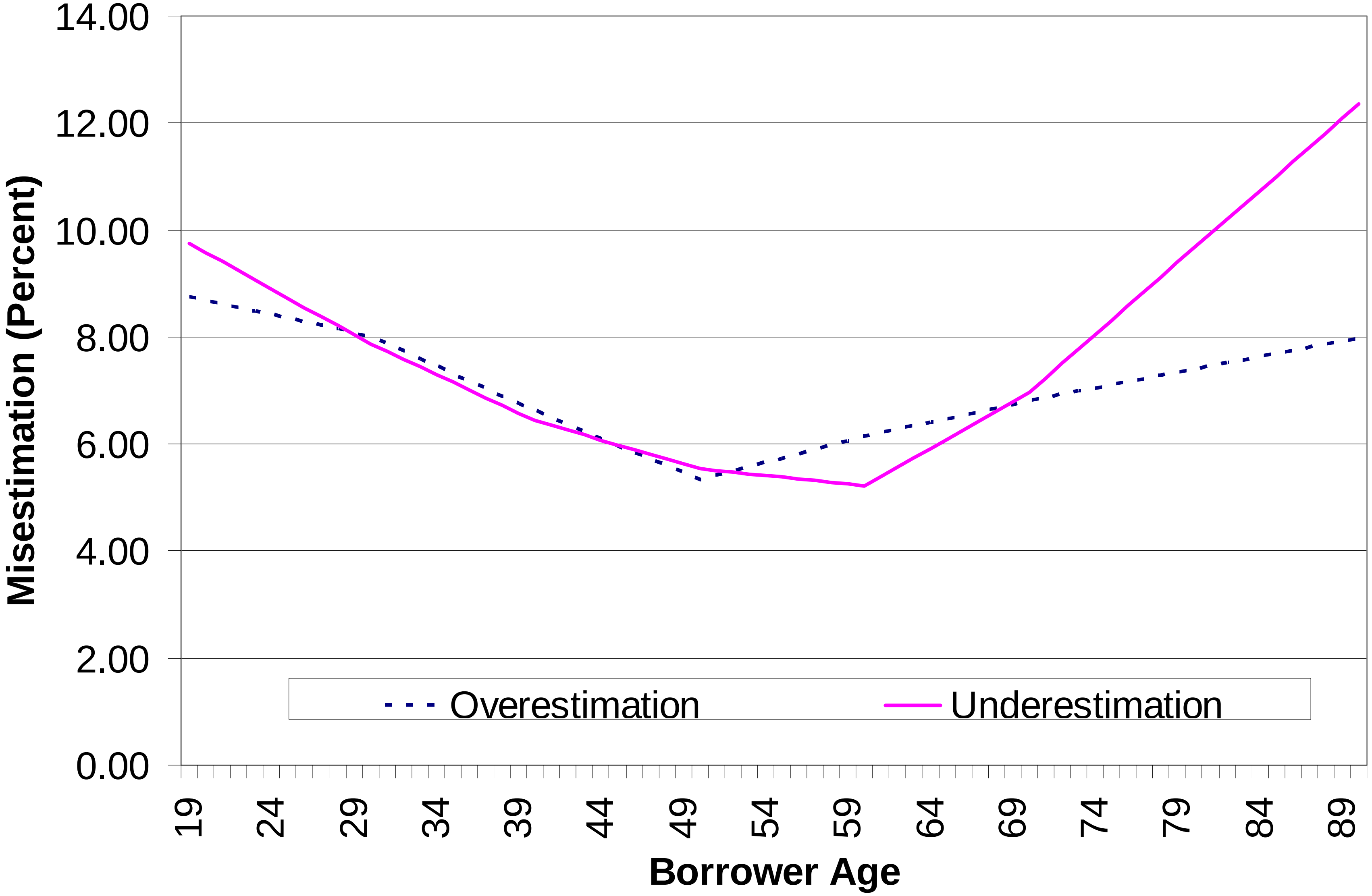


Figure 6: Under- and Over- estimation of House Value by Borrower Age



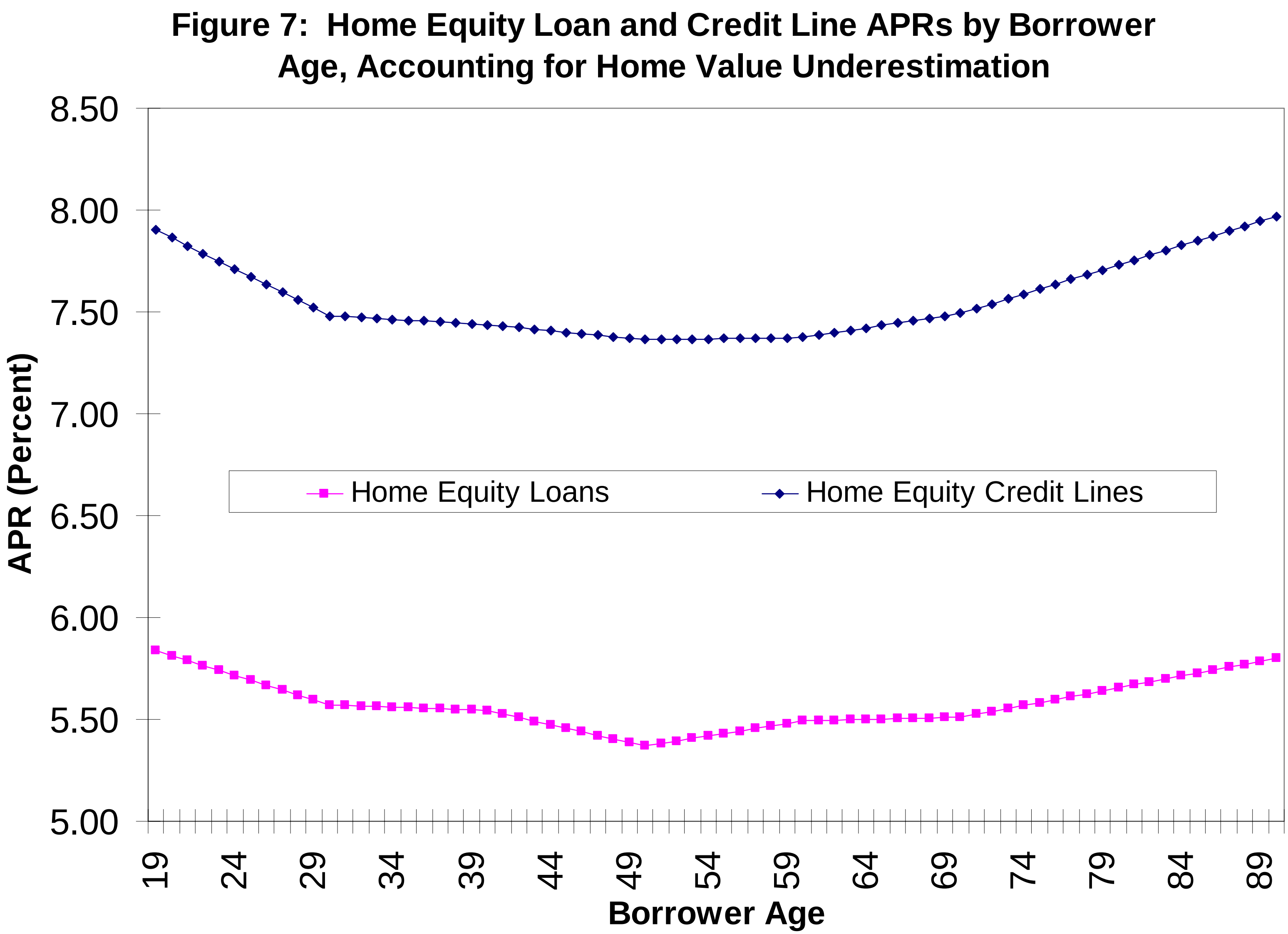


Figure 7: Home Equity Loan and Credit Line APRs by Borrower Age, Accounting for Home Value Underestimation
APR (Percent)
8.50
8.00
7.50
7.00
6.50
6.00
5.50
5.00
Home Equity Loans
Home Equity Credit Lines
19
24
29
34
39
44
49
54
59
64
69
74
79
84
89
Borrower Age

Figure 8: Credit Card APRs by Borrower Age

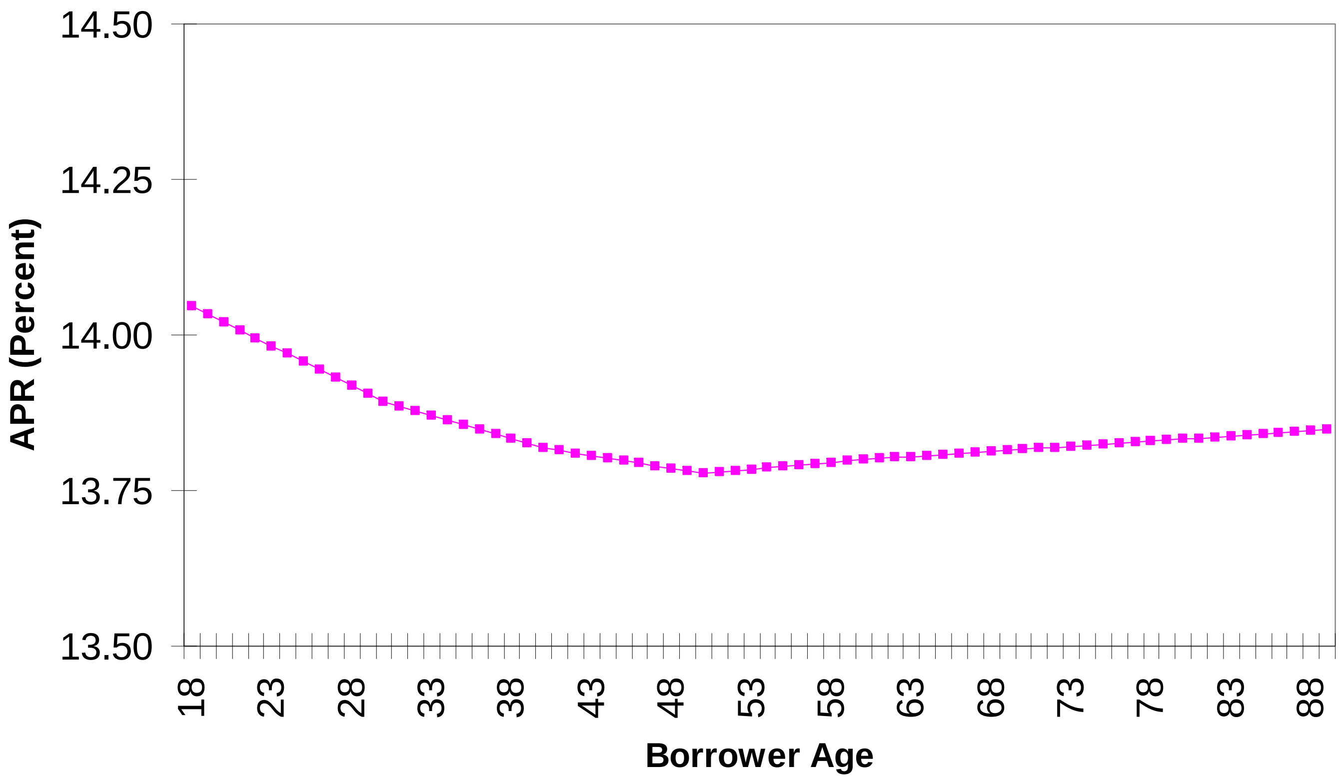


Figure 9: Auto Loan APR by Borrower Age

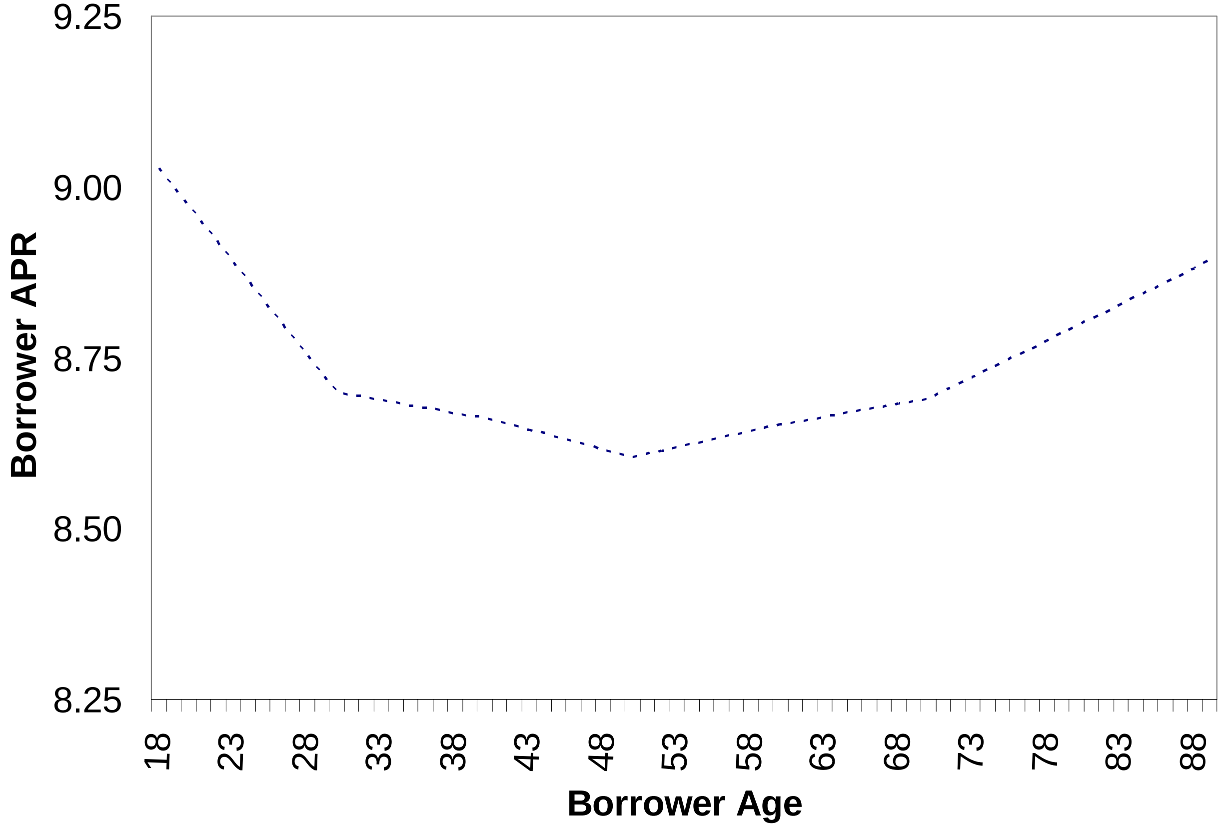


Figure 10: Argentine Mortgage APRs by Borrower Age

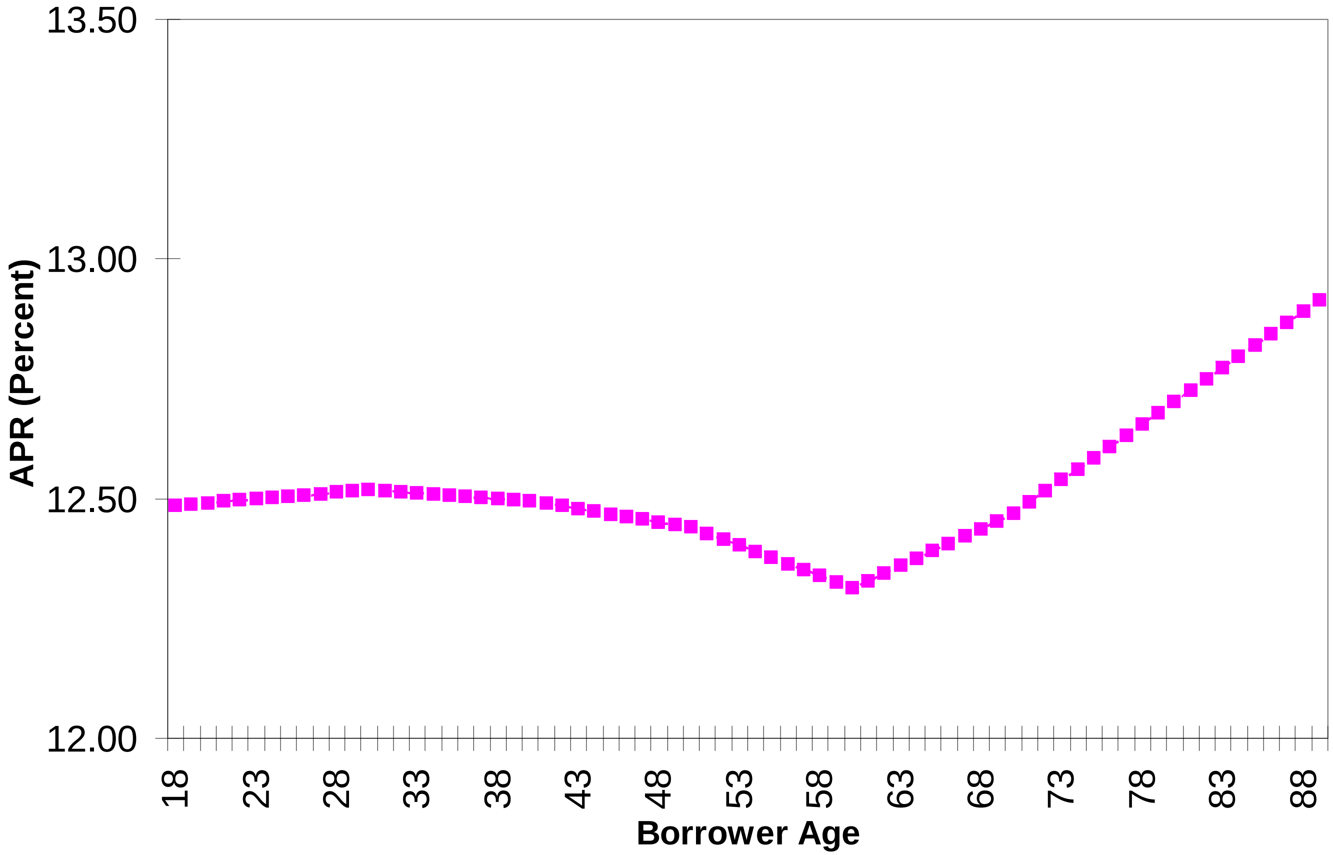


Figure 11: Small Business Credit Card APR by Borrower Age

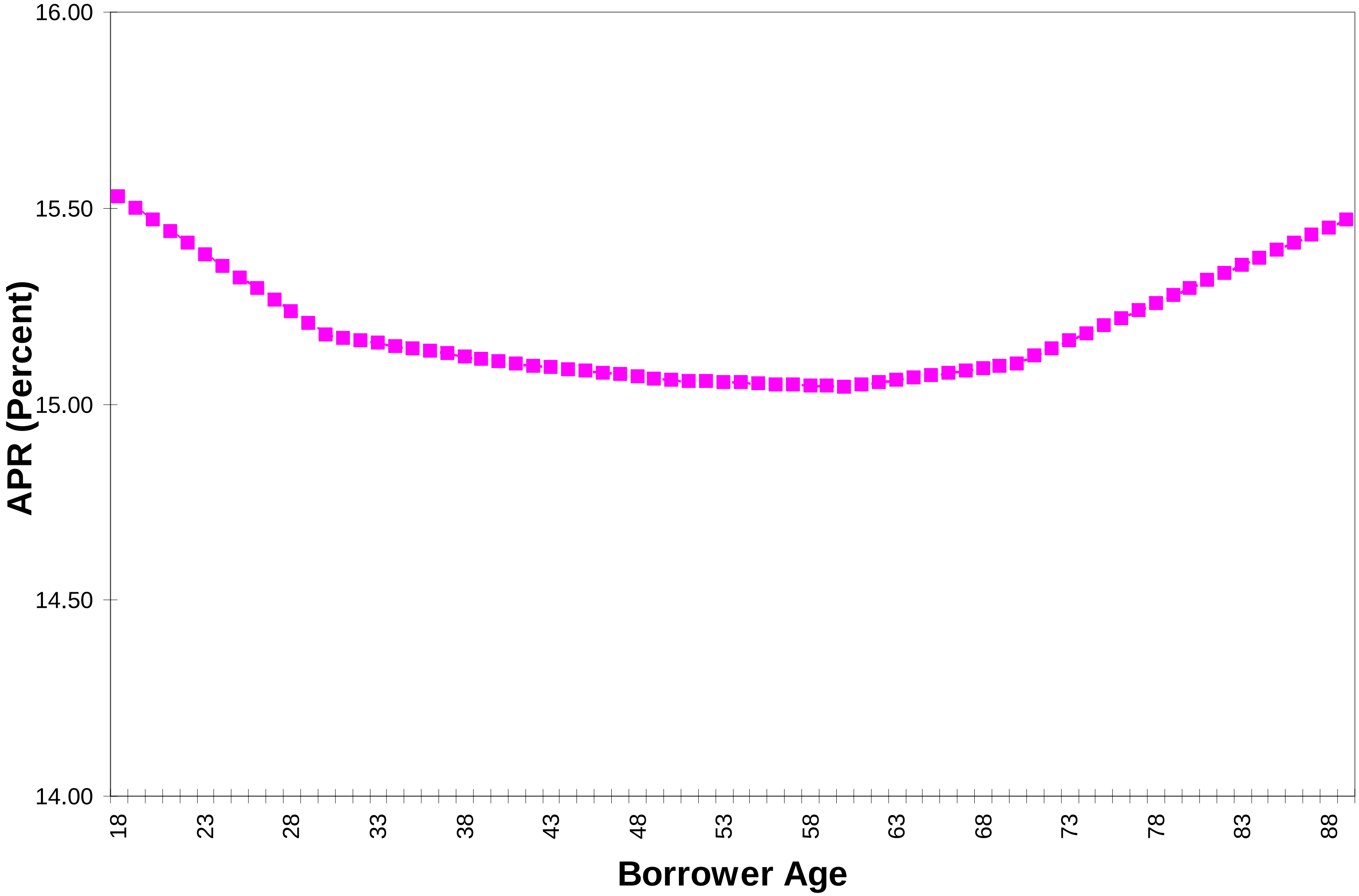


Figure 12: Default Rates by Borrower Age