The Costs of Financial Mistakes:
Evidence from U.S. Consumers[*]

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Abstract

This paper investigates the relationship between financial mistakes and lack of consumption smoothing, using transaction-level data from a million U.S. consumers. I first document that, even in my sample of relatively sophisticated consumers, simple and avoidable card fees are pervasive and persistent. Avoidable fees correlate with lower account optimization, lower participation in risky asset markets, and lower mortgage refinancing. I measure the marginal propensity to consume using an event study of mortgage payment resets and a difference-in-differences methodology. Consumers with a history of frequent financial mistakes display low consumption smoothing out of predictable increases in debt payments, counter to models with rational borrowing constraints. Guided by these results, I compare different economic mechanisms that link financial mistakes and lack of consumption smoothing: the evidence is more supportive of financial ignorance rather than rational information inattention. A calibrated model of financial ignorance indicates that for the 10% of consumers who make the most mistakes, the welfare loss amounts to $1,740 per year, equivalent to 8% of median annual non-durable consumption.

*"A year before the housing meltdown, Richard Peterson took out a $167,000 credit line on his Huntington Beach condo. ... Peterson, 62, who has since retired, received his **unpleasant shock** last month. ... (H)is payment will rise to more than $1,100 a month from the $400 he is paying to cover just the interest. 'We both now live on a fixed income and will not be able to make the payments,' he said of himself and his girlfriend."*

LA Times, 8/7/2014: *"Home equity line defaults are likely to rise"*.

1 Introduction

Why don't consumers smooth consumption? A central finding in macroeconomics and finance is consumers display a significant consumption response to *predictable* changes in income, counter to the canonical life-cycle/permanent-income hypothesis (LC/PIH), with the strongest effect concentrated among consumers with low liquidity.[1] Understanding what drives lack of consumption smoothing is critical both for theoretical evaluations of models of consumption, as well as for empirical estimations of the macroeconomic effects of fiscal and monetary policy.[2]

Research presents two contrasting views on what causes low liquidity and lack of consumption smoothing. The long-held conventional view is consumers have homogeneous preferences and rational expectations. According to this view, lack of consumption smoothing and low liquidity is a consequence of idiosyncratic and uninsurable income shocks and rational liquidity management. For example, both the textbook buffer-stock models, as well as recent models with multiple assets, predict that a high marginal propensity to consume (MPC) out of predictable income is situational and caused purely by temporarily low liquidity. However, according to the alternative view, low liquidity and lack of consumption smoothing are due to persistent differences in behavioral characteristics. These differences may include, for example, the degree of impatience, differences in attention to information, or – as I will argue in this paper – differences in consumers' ability to make financial decisions and financial plans.[3]

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[1]A large body of empirical literature, going back at least to Zeldes (1989), has documented a high marginal propensity to consume (MPC) out of predictable changes in income. Recent papers have studied the response to social security tax withholdings (Parker, 1999), income tax refunds (Souleles, 1999; Johnson, Parker and Souleles, 2006; Parker, 2015), paycheck receipts (Stephens, 2006), and predictable decreases in loan payments (Stephens, 2008; Di Maggio et al., n.d.). See the literature review for additional papers, and see Jappelli and Pistaferri (2010) for a recent survey.

[2]For example, MPC estimates from Johnson, Parker and Souleles (2006) are cited prominently by the Congressional Budget Office and the Council of Economic Advisers in their evaluation of the fiscal stimulus following the financial crisis (CBO, 2009; CEA, 2010). Additionally, recent work by Auclert (2016) and Wong (2015) argue that differences in MPCs have a first-order impact on the effectiveness of monetary policy.

[3]The seminal papers on the conventional view of household consumption under incomplete markets include Bewley (1977), Deaton (1991), Huggett (1993), Aiyagari (1994), and Carroll (1997), and recent papers building on these include Kaplan and Violante (2014) and Kaplan, Moll and Violante (2016). Research on the alternative view includes Mankiw and Campbell (1989), Caballero (1995), Lusardi (1999), Hurst (2003), and Reis (2006). See Parker (2015) for a review of the two views on what drives lack of consumption smoothing.

In this paper, I provide empirical evidence in favor of the behavioral view. I propose and test the hypothesis that lack of consumption smoothing reflects a persistent tendency to make financial mistakes. We have theoretical reasons to believe poor financial planning can lead to lack of consumption smoothing.[4] However, various empirical challenges complicate investigation of this hypothesis, and despite rigorous efforts, the effect of financial mistakes on consumption smoothing remains largely unknown. The empirical challenges include both data- and measurement-related challenges as well as difficulties in inferring causation due to omitted variables. In this paper, I address these empirical challenges using a unique and detailed database of both account and card transactions from U.S. consumers. I measure financial mistakes and use variation in predictable increases in debt payments to assess how these mistakes relate to consumption smoothing. My tests allow me to compare different economic mechanisms that link financial mistakes and lack of consumption smoothing. I then develop a calibrated model of financial ignorance to assess the welfare losses due to financial mistakes.

I start my empirical analysis by documenting that financial mistakes are pervasive and persistent. I face a key empirical challenge when measuring financial mistakes. Because comprehensive micro data have been previously unavailable, disentangling financial mistakes from rational liquidity demands has been difficult in past work.[5] I counter this problem by using the unique merge of both daily deposit balances and daily card transactions.

I define a financial mistake, as a financial decision where an unambiguous optimal choice exists, and where the consumer does not choose the optimal choice.[6] In my benchmark analysis I analyze two unambiguous financial mistakes: incurring an avoidable late fee, and incurring an avoidable overdraft fee. Following Stango and Zinman (2009) and Scholnick, Massoud and Saunders (2013), I define a late fee as avoidable, if on the payment day, the consumer had sufficient balances in his deposit account to cover both the minimum balance and an average month of consumption expenditure. Similarly, I define an overdraft fee as avoidable, if on the day the expenditure occurred, the consumer had sufficient liquidity (in deposit accounts and on other cards) to cover both the purchase and an average month of consumption expenditure.

I show that even in my sample of relatively sophisticated consumers, more than two thirds of consumers incur avoidable card fees. The cost of these mistakes can vary quite a bit, with

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[4]Conceptually, many of the psychological mechanisms underpinning financial mistakes, such as optimization mistakes and lack of sophistication, are also prevalent among consumers who display lack of consumption smoothing (Parker, 2015).

[5]Telyukova (2013) argues that the coexistence of high interest rate credit card debt and low interest-bearing deposits can be rationalized by expenses that can only be paid in cash.

[6]The literature on household finance has identified numerous consumer choices that are hard to rationalize using models of optimal choice (see Campbell (2016)). These choices include both extreme decisions, with unambiguously optimal choices, and more complex decisions where the optimal choice is potentially sensitive to individual consumer circumstances. The former unambiguous choices include, for example, incurring avoidable overdraft fees, and the latter more complex choices include, for example, lack of mortgage refinancing.

around 20% of the consumers incurring mistakes that result in fees that range between $200 and $950 annually.[7] These fees are also persistent over time. For example, the probability of incurring an avoidable late fee is only 22% if one didn't incur any avoidable late fees in the previous year. However, the probability of incurring an avoidable late fee increases to 64% if one incurred at least one late fee in the previous year, and the probability increases to 92% if the consumer ranked in the top decile based on avoidable fees in the previous year.

My second and main empirical finding is consumers who frequently make financial mistakes also display a lack of consumption smoothing. The main empirical challenge here is that consumers who make financial mistakes often have low and uncertain incomes, and few or no financial assets, and thus they are often borrowing constrained. Therefore, inferring whether lack of consumption smoothing is the result of rational borrowing constraints or irrational financial mistakes is difficult. I address this challenge by using a predetermined, *negative change* in disposable income. Even a liquidity-constrained consumer - presuming some degree of rationality - will save for predictable negative income changes. This asymmetry in the borrowing constraint, noted by Zeldes (1989), offers a concise method to isolate whether the relationship one finds might be beyond rational borrowing constraints.[8]

In my analysis I use a predictable increase in the monthly mortgage payments for consumers who have taken out interest-only home equity lines of credit (IO-HELOCs). After a predetermined draw period, IO-HELOCs convert from open-ended interest-only loans, to close-ended amortizing loans. This institutional design ensures borrowers face a sharp discontinuity in their monthly payments after the draw period. The median monthly change in the sample is above $500 per month. It is worth emphasizing that despite the high stakes and the perfectly predictable reset date, anecdotal evidence suggests many consumers are unaware of the contractual features of their HELOCs. For instance, in a 2016 survey, TD Bank found that more than one quarter of homeowners with HELOCs did not know when their HELOC draw period end (TD Bank, 2016). Relatedly, only 19% knew the monthly payment increases when the draw period ends, and, surprisingly, 38% of those surveyed thought their payments would decrease.

My tests use an event study of *predictable increases* in debt payments employing a difference-in-differences research design. To implement this test, I sort consumers by their history of mistakes at the end of the HELOC draw period. The "control" group are consumers who, up until the reset date, have never incurred any avoidable late or avoidable overdraft fees.

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[7]It is worth noting that though the cost of the benchmark mistakes (avoidable late and overdraft fees) may be relatively small (less than $100 per year for the median consumer), we study them because they unambiguously show that consumers differ in their ability to make financial decisions that might be quite costly. These include decisions such as lack of account optimization, lack of stock market participation, and lack of mortgage refinancing.

[8]Jappelli and Pistaferri (2010) note in their review article that only a few empirical papers study income drops other than retirement. Recent examples include Baker and Yannelis (2017) and Gelman et al. (2015), who examine the spending response to loss of income following the federal government shutdown, and Ganong and Noel (2016), who study consumption around the expiration of unemployment benefits.

This group accounts for approximately 30% of the sample. I sort the remaining consumers in quartiles based on frequency of the two benchmark mistakes, measured just prior to the reset. The "treatment" group is the highest quartile, approximately 17% of the entire sample.

I show that the treatment and control group are similar, in terms of age, income, unemployment rate over past six months, and change in income over past six months. For example, the average income in the control group is $98,164 and $97,285 in the treatment group, and in both groups the average unemployment rate in the past six months was 2%. The two groups also display similar credit scores. According to the bank's internal credit score, the control group had a score of 339 and the treatment group a score of 337 (out of 380). In addition, the two groups display similar consumption expenditure, prior to the reset date. The average monthly expenditure was $1,901 and $1,912 for the control and treatment group, respectively. The two groups are similar in the period before the event, not only on average but also period by period.

A difference-in-differences research design reveals significant heterogeneity in the MPC across measures of prior financial mistakes. For example, consumers with no history of avoidable card fees smooth their consumption expenditure around the payment reset. This behavior is in line with predictions from rational models. However, consumers with a history of frequent mistakes cut their consumption expenditure by almost 9% following the payment resets. Consumers cut their consumption across both durable and non-durable goods. The largest one-month cuts occur in the categories of travel (-$27), auto durables (-$26), healthcare (-$23), and restaurants (-$19). The difference in consumption sensitivity across the two groups is robust to relaxing the threshold for what constitutes a financial mistake. For example, if we sort on all late and overdraft fees, not just avoidable fees, we see an even larger drop ($254).

Having established evidence in favor of behavioral view, when explaining the relationship between financial mistakes and lack of consumption smoothing, the last part of my paper investigates the economic mechanisms behind this link. I test two types of hypotheses: models of rational time constraints and models of financial ignorance. Using data on online and mobile logins, I find financial mistakes are positively correlated both with access to online accounts and with frequency of logins, even after controlling for age. This finding contradicts models in which time is the scarce resource preventing consumers from avoiding the fees. Next, I test whether financial mistakes are correlated with financial ignorance, as proxied by measures of education. I use the shares of households in a ZIP who have completed at least high school, 2-year college, and 4-year college, respectively, as proxies for the education of the consumers, and I find these proxies for education are negatively correlated with the frequency of mistakes. For example, controlling for the income of the consumer, in ZIP codes where many households have attained at least a 4-year college degree, the frequency of mistakes is lower. Overall, these tests are more consistent with consumers with financial mistakes also being financially ignorant.

In the last part of my paper, I estimate welfare consequences of financial mistakes by calibrating a consumption-savings model in which financial mistakes are the result of financial ignorance. I micro-found the financial ignorance as a result of "cognitive sparsity" (Gabaix, 2014, 2016b). This assumption of "cognitive sparsity" can both generate the per-period cost of avoidable fees, as well as the lack of consumption smoothing around predictable debt-payment changes. Quantitatively, I calibrate the model to the HELOC expenditure profiles. I find that avoiding simple financial mistakes can save the median consumer $130 per year and save the 10% of consumers with the most mistakes an average of $1,740 per year, which is equivalent to 8% of median annual non-durable consumption.

Interestingly, the model generates an additional and testable qualitative implication: consumers are systematically wrong in their expectations of future liabilities from the interest-rate reset. That is, consumers who are ignorant of the contractual features of the HELOC will under-estimate the value of future liabilities. In other words, ignorant consumers will believe they are wealthier than they are. I test this hypothesis by categorizing the type of expenditure into luxury and necessity, and by calculating Engel curves. I find that consumers who frequently make mistakes have a higher expenditure ratio on luxury goods, especially following increased credit limits.

My findings have both conceptual and practical implications. In terms of conceptual implications, my findings suggests differences in consumption smoothing can be attributed to financial ignorance, in a similar spirit to a nascent literature documenting that lack of consumption smoothing is related to persistent behavioral characteristics (Parker, 2015; Gelman, 2017, 2016). The specific finding that mistakes correlate across multiple domains suggests the psychological mechanism underpinning simple mistakes also distorts more complex decisions. In addition, my findings suggest the sparsity tools from statistical learning (Tibshirani, 1996; Gabaix, 2014) are useful when modeling financial ignorance. Financially ignorant consumers can be modeled as assigning no attention to future interest-rate changes.

In terms of practical implications, my research adds to a growing empirical literature, measuring the welfare cost of financial mistakes (Agarwal et al., 2009; Calvet, Campbell and Sodini, 2007; Lusardi and Tufano, 2015; Keys, Pope and Pope, 2016). Additionally, the benchmark financial mistakes studied in this paper are simple and avoidable, and leave scope for financial products that "nudge" consumers (Thaler and Sunstein, 2008), for example, auto-payment systems to avoid credit card fees. However, the paper also finds that mistakes correlate across multiple domains where "easy fixes" can prove insufficient, which leaves financial regulators with a difficult tradeoff when weighing the benefits of regulation to the consumers who make mistakes against the costs of regulation to other financial market participants, as discussed by Campbell (2016).

Related literature

This paper builds on several related strands of literature in household finance, consumption theory, and behavioral economics. Within household finance, this paper contributes to the literature on financial mistakes within credit and debit cards (Stango and Zinman, 2009, 2014; Agarwal et al., 2009, 2013, 2015*b*,*c*; Scholnick, Massoud and Saunders, 2013; Gathergood et al., 2017; Ponce, Seira and Zamarripa, 2017). More broadly, this paper contributes to a growing literature on financial mistakes. This literature goes back at least to Bernheim (1995, 1998), who was among the first to show most households cannot perform very simple calculations and lack basic financial knowledge. Subsequent empirical work includes research on mistakes within savings and investment (Madrian and Shea, 2001; Barber and Odean, 2004; Calvet, Campbell and Sodini, 2007; Choi, Laibson and Madrian, 2011), financial literacy (Lusardi and Mitchell, 2007*b*,*a*; Lusardi and Tufano, 2015; van Rooij, Lusardi and Alessie, 2011*b*; Klapper, Lusardi and Panos, 2013), mistakes on mortgages (Andersen et al., 2015; Keys, Pope and Pope, 2016; Agarwal, Ben-David and Yao, 2017), and mistakes in adjusting to taxes (Chetty, Looney and Kroft, 2009; Finkelstein, 2009). Campbell (2016) is a recent survey of the literature on financial mistakes, and Lusardi and Mitchell (2014) offer a survey of the literature on financial literacy.

A large theoretical literature investigates the determinants of consumption behavior. The seminal work by Bewley (1977), Deaton (1991), Huggett (1993), Aiyagari (1994), and Carroll (1997) introduced the framework of consumption in incomplete market economies. Under this framework, consumers smooth consumption from idiosyncratic and uninsurable income shocks subject to a borrowing constraint. In these models, the agent has rational expectations and perfectly understands the impact of her financial decisions. With homogeneous consumers, a high MPC is a rational consequence of the uninsurable income risk and a borrowing constraint. These models thus mark a departure from the classic PIH/LCI, which predicts a zero-consumption response to predictable changes in income. Many recent papers have highlighted the aggregate implications arising from heterogeneity in MPCs across the household population (Eggertsson and Krugman, 2012; Kaplan and Violante, 2014; Guerrieri and Lorenzoni, 2015; Wong, 2015; Auclert, 2016; Greenwald, 2016). Two notable exceptions that depart from the assumption of perfect rationality are Gabaix (2016*a*) and Farhi and Werning (2017). Both papers augment New Keynesian models with bounded rationality in the form of sparsity and level-*k* thinking, respectively. This paper contributes to the theoretical literature with empirical evidence on the empirical role of bounded rationality.

Concurrent with the theoretical literature, this paper also contributes to the empirical literature on consumer theory, which documents empirically that household consumption departs from the standard LC/PIH model predictions. A large body of literature going back at least to Zeldes (1989) has studied the role of borrowing constraints on household consumption, and found consumption responds to predictable changes in income in a manner

suggesting the relevance of borrowing constraints. This literature includes studies of social security tax withholdings (Parker, 1999), income tax refunds (Souleles, 1999; Johnson, Parker and Souleles, 2006; Parker, 2015), paycheck receipts (Stephens, 2006; Olafsson and Pagel, n.d.), job losses (Baker, 2017), and predictable decreases in loan payments (Stephens, 2008; Di Maggio et al., n.d.). However, a number of studies find no evidence in favor of borrowing constraints (Hsieh, 2003; Coulibaly and Li, 2006). Recent studies that have found substantial heterogeneity in MPCs include studies of income shocks (Parker et al., 2013; Jappelli and Pistaferri, 2014) and studies of MPCs out of shocks to housing prices and wealth (Mian and Sufi, 2011; Mian, Rao and Sufi, 2013). The literature on consumption responses and borrowing constraints is also often used by policy makers to determine the effectiveness of monetary and fiscal policy (CBO, 2009; CEA, 2010).

Similar to Baker (2017), Olafsson and Pagel (n.d.) use data from a personal finance app from Iceland and find that many households display consumption responses around paycheck receipts. These findings are also hard to rationalize with standard liquidity constraints, as the authors simultaneously observe sufficient liquidity from bank accounts. Olafsson and Pagel (n.d.) argue that these results are not driven by financial sophistication, proxying, among other things, with age and number of logins. However, in this paper I find that both age and number of logins are not linearly related to sophistication. I find that mistakes have a u-shaped relationship with financial mistakes and that the number of logins are positively related to the frequency of financial mistakes, and I find that the frequency of incurring financial mistakes is negatively related to measures of education. In addition, my paper calibrates a model of financial ignorance and tests an out-of-sample prediction of financial ignorance: In line with the models predictions, I find that consumers who incur frequent financial mistakes spend a higher fraction of their total consumption on luxury goods, such as travel, electronics, arts and jewelry.

The HELOC interest rate reset studied in this paper contributes to recent research which have studied the MPC out of negative changes in income. For example, Ganong and Noel (2016) study consumption around the expiration of unemployment benefits. They also find a negative consumption response, counter to rational models. Baker and Yannelis (2017) and Gelman et al. (2015) examine the spending response to an unanticipated, temporary loss of income: the federal government shutdown.

Within behavioral economics, this paper contributes to the broad literature on market interactions between rational and non-rational agents: Akerlof and Yellen (1985); De Long et al. (1990); Tirole and Benabou (2003); DellaVigna and Malmendier (2004); Gabaix and Lalisbon (2006). For example, DellaVigna and Malmendier (2004) analyze the contract design of firms when consumers are time-inconsistent and partially naive. Among other markets – and related to this paper – they analyze the market for credit card-financed consumption (a market with immediate benefits and delayed costs). They find credit card issuers will price above

marginal cost, introduce switching costs, and charge back-loaded fees. Another related paper is Vissing-Jørgensen (2012). Here the author uses detailed data from Mexico and shows the type of purchase has predictive power for default. As in this paper, the author finds that goods associated with high loss rates tend to be luxuries and tend to be purchased by individuals who consume abnormally large fractions of luxuries given their income.

Outline

The rest of the paper is structured as follows. Section 2 covers the institutional background and describes the data. Section 3 calculates the frequency of avoidable card fees and tests whether such fees are valid measures of financial mistakes. In section 4, I analyze the impact of financial mistakes on consumption smoothing. In section 5, I compare theories of financial mistakes and calibrate a model of financial ignorance, and section 6 concludes.

2   Background and Data

In this section, I describe the institutional background and data sources used in the empirical analysis. The empirical design relies on contractual details of credit and debit card fees and the repayment structure of the HELOC. Fist, I describe the landscape of U.S. credit and debit card fees and describe the two fees I will use in the benchmark analysis: the late fee and the overdraft fee. I then describe the HELOC. Lastly, I present the specific data set used in the paper, built in collaboration with a large U.S. financial institution.

In my benchmark analysis, I measure the frequency of avoidable late and overdraft fees. As I will show below, both late and overdraft are common. The majority of U.S. banks impose both late and overdraft fees, and a large fraction of the population have incurred at least one these fees.

2.1   Consumer banking and card fees

Credit and debit cards function as a method of payment and as a source of unsecured consumer credit for a large part of the U.S. population. According to the U.S. Census Bureau, 160 million card holders held more than a billion credit cards in 2012. The financial institutions that issue credit and debit cards earn an income on the cards – generally speaking – through two different sources: interest income and fees. Interest is earned on unpaid consumer debt, and fees are levied partly on the consumers and partly on the merchants as a transaction fee. In aggregate, the income for U.S. financial institutions from credit card fees have long surpassed income from interest on credit card debt (see figure A1).

The most common fees imposed on consumers from credit cards include annual fees, balance-transfer fees, cash advance fees, foreign transaction fees, over-the-limit fees, late, and

returned check fees. Common debit card fees imposed on consumers include annual or monthly fees, atm fees, and overdraft and not-sufficient-funds (NSF) fees. According to the CFPB, revenues from consumer overdraft and NSF fees totaled $11.16B in 2015.

In this paper, I use data on two of the most common fees: the late fee, which is imposed on missing credit card payments, and the overdraft fee imposed on debit card transactions with insufficient funds. Both the late fee and the overdraft fee are common in the United States: According to a survey by creditcards.com, 99 out of 100 general-purpose credit cards impose a late fee, with an average late fee of $37.[9] According to a survey by nerdwallet.com of 30 U.S. financial institutions, all 30 charge an overdraft fee.[10] Among credit card fees, other common fees include cash-advance fees (98 out of the 100 cards surveyed), returned-payment fees (77/100), balance-transfer fees (77 out of 89 cards that allowed balance transfers in 2016), and foreign-transaction fees (61/100). Only 25 and 6 of the cards surveyed imposed an annual fee and an overlimit fee, respectively.

The Credit Card Accountability Responsibility and Disclosure (CARD) Act of 2009 capped the size of late fees at $25 for the first instance and $35 for each additional late payment within six months. However, under the CARD act, the limits are subject to an annual adjustment based on a federal consumer price index, and the maximum late fee has been adjusted to $38 in 2017 by the CFPB. If a consumer goes six months without another late payment, the account resets to the lower first-time fee.

On top of the *direct* cost through the fee, a late payment can also impose an *indirect* cost on the consumer through a so-called *penalty APR*. The penalty APR is a higher interest rate that is imposed if the consumer violates the terms of the contract. A common "trigger" of the penalty APR is a late payment or exceeding one's credit limit. While the national average credit card APR for the first six months of 2017 was 15.5%,[11] the median penalty APRs was 29.99%. The CARD act also imposed restrictions on how and when financial institutions can impose a penalty APR.[12] The financial institution can impose a penalty APR on future purchases (i.e., not on the existing balance) for any reason – including a missed payment – once the account has been open for at least 12 months. If the interest rate that applies to future transactions is changed, the financial institution is required to notify the consumer 45 days in advance, specifying the reason for the rate increase, and the rate increase can only apply to purchases made 14 days after the notice was sent. Additionally, a financial institution can only increase the interest rate on an existing balance if the customer is 60 days delinquent

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[9]See `http://www.creditcards.com/credit-card-news/2016-card-fee-survey.php` (accessed on 8/16/2017).

[10]See `https://www.nerdwallet.com/blog/banking/overdraft-fees-what-banks-charge/` (accessed on 8/16/2017).

[11]According to CreditCards.com's monthly report: `http://www.creditcards.com/credit-card-news/interest-rate-report-81617-up-2121.php`

[12]Agarwal et al. (2015c) study the effect of the CARD act, and find that regulatory limits on credit card fees reduced overall borrowing costs with no evidence of an offsetting increase in interest charges or a reduction in the volume of credit. Taken together, they estimate the CARD Act saved consumers $11.9 billion a year.

on making a minimum payment. Finally, the credit card issuer is required to terminate the penalty APR after no more than six months after the date it was imposed, if the consumer has paid all the minimum payments during that period.

In table A1 in the appendix, I have tabulated the average fee costs from six leading U.S. financial institutions for late fees, overdraft fees, and penalty APRs.

2.2 Home equity lines of credit

In my main empirical analysis, I measure the MPC out of a predictable and negative change in disposable income. I use a specific contractual detail from a mortgage product called a home equity line of credit (HELOC), to generate this event study. A HELOC is a credit line given to a homeowner and for which the residence is used as security. When issuing a HELOC, the lender provides a line of credit up to a maximum draw amount, for example, $50,000 or $100,000. The consumer can draw on the HELOC using either a specially issued credit card, writing a check, or in other ways.

Most HELOCs are structured with a *draw* period and a *repayment* period. During the draw period, which usually lasts 5, 10, or 20 years, the HELOC is an open-ended non-amortizing line of credit, which means the consumer is only required to pay interest on the outstanding principal balance. After the draw period ends and the repayment period begins, the HELOC converts to a close-ended, amortizing loan. During the repayment period, the borrower must pay down the principal by making payments equal to the balance at the end of the draw period divided by the number of months in the repayment period. Most repayment periods last 10 to 20 years; however, some HELOCs are structured with a single full prepayment of the principal at the end of the draw period through a so-called "balloon" payment, at which point most borrowers refinance the loan. Johnson and Sarama (2015) study data from the FRY-14M regulatory report and the CoreLogic Loan Performance Home Equity Servicing data, and they find HELOCs with balloon payments are more prevalent among riskier households with low FICO scores and high cumulative loan-to-value ratios (CLTV). To avoid this selection bias, I exclude all HELOCs with baloon payments from my sample.

Many HELOCs were issued in the early and mid 2000s, and many of the outstanding HELOCs converts in the mid to late 2010s. As macroeconomic conditions, in particular house prices, improved following the crisis, the aggregate losses on HELOCs have been muted. Note that since the financial crisis, many financial institutions have changed parts of their HELOC product features, for example, some HELOCs issued in 2017 require partial amortization in the years leading up to the interest rate reset, and several financial institutions have begun actively reaching out to their consumers and reminding them of the upcoming payment reset.

Johnson and Sarama (2015) document an increased default risk following the conversion, and the increased risk has also been cited in the financial press.[13] An article in the *LA Times*

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[13]Rieker (2014); Gittelsohn (2013); Jurow (2016).

([Khouri and Scott, 2014](#)) features a borrower who appears surprised by the loan conversion (emphasis mine):

> "A year before the housing meltdown, Richard Peterson took out a $167,000 credit line on his Huntington Beach condo. ... Peterson, 62, who has since retired, received his **unpleasant shock** last month in a letter from Specialized Loan Servicing, the company that collects his mortgage payment. As of July 2016, his payment will rise to more than $1,100 a month from the $400 he is paying to cover just the interest. "We both now live on a fixed income and will not be able to make the payments," he said of himself and his girlfriend."

This paper complements [Johnson and Sarama](#) ([2015](#)) by analyzing how customers who have a history of financial mistakes appear *surprised* like Mr. Peterson: I find that customers with a history of financial mistakes (measured as the frequency of avoidable card fees) have a higher delinquency rate following the loan conversion.

2.3   Description of bank data

In collaboration with a large U.S. financial institution I have created a data set that allows me to jointly study financial choices and expenditure choices. The data are solely from this institution, which I will refer to as "my bank," and the data set is de-identified. The data set is constructed using consumer data from 2012 to 2017. It includes transaction-level data from checking and savings accounts, credit and debit card transactions, data on mortgage acccounts, and estimates of total asset holdings. For my main analysis, I restrict my sample to "active" consumers. My bank defines an active consumer as a consumer who has had at least five monthly deposit-account outflows at some point. I further restrict the sample to only consider consumers who also have at least one active credit card with the bank. An active credit card is defined as a card that at some point has had at least five monthly transactions. From these two restrictions, I draw a random sample of 1 million consumers. Hence, I am analyzing a sample of 1 million bank customers who have both an active deposit account and an active credit card with the same institution. Additionally, for the analysis of MPC differences, I construct a sample of consumers with both an active deposit account and an active credit card and who hold a HELOC. This second sample has 320,000 consumers.

For each consumer, the data set includes a number of daily and monthly observations. The daily observations from the financial institution include transactions from credit and debit cards and transactions from checking and savings accounts. Monthly data from the institution include balances and interest rates from checking and savings accounts, the internal bank credit score, and the institutions own monthly estimates of total asset holdings. For the consumers who hold a HELOC, the data set also includes additional variables related to their

HELOC. The HELOC variables are updated at a monthly frequency and the include original balance, credit line, interest rate, outstanding balance, and debt payments.

The main variables of interest are spending, income, assets, and liabilities. Below, I describe how I construct each of these four variables. I construct the measure of spending, which captures 50% of all outflows from checking accounts from three components. The first component is debit and credit card spending, where I classify the month of credit card spending as the month in which the expenditure occurs, not the month in which the credit card bill is paid. The second component is cash withdrawals, and the third is bill payments. The other 50% of outflows are made up of consumer debt payments, transfers to external accounts, and uncategorized outflows. The second main variable is income. I construct income from two components that jointly make up 60% of inflows: (1) payroll paid using direct deposits and (2) government income. The remaining inflow categories include transfers from savings and investment accounts, other income, and uncategorized inflows. I use two measures of assets: total assets and liquid assets. My bank has a measure of total assets based on an internal statistical model, which uses a combination of checking-account activity, transfers to investment accounts, and third-party data sources. The measure of liquid assets is constructed from balances on savings and checking accounts within the bank. Finally, I construct a measure of liabilities, using outstanding revolving balances on credit cards within the bank. The unit of observation for all five variables is consumer-by-month, from November 2012 through June 2017.

3   Financial Mistakes

The literature on household finance has identified numerous consumer choices that are hard to rationalize using models of optimal choice (see Campbell (2016)). These choices include both extreme decisions, with unambiguously optimal choices, and more complex decisions where the optimal choice is potentially sensitive to individual consumer circumstances. The former unambiguous choices include, for example, incurring avoidable overdraft fees, and the latter more complex choices include, for example, lack of mortgage refinancing.

In this paper, I define a financial mistake, as a financial decision where an unambiguous optimal choice exists, and where the optimal choice is not chosen by the consumer. In my benchmark analysis I analyze two unambiguous financial mistakes: incurring an avoidable late fee, and incurring an avoidable overdraft fee. Following Stango and Zinman (2009) and Scholnick, Massoud and Saunders (2013), I define a late fee as avoidable, if on the payment day, the consumer had sufficient balances in his deposit account to cover both the minimum balance and an average month of consumption expenditure. Similarly, I define an overdraft fee as avoidable, if on the day the expenditure occurred, the consumer had sufficient liquidity (in deposit accounts and on other cards) to cover both the purchase and an average month of

consumption expenditure.

Given this definition of a financial mistake, I show that even in a sample of relatively sophisticated consumers, financial mistakes are pervasive – more than two thirds of consumers incur avoidable card fees – and persistent. For example, the probability of incurring an avoidable late fee is only 22% if one didn't incur any avoidable late fees in the previous year. However, the probability of incurring an avoidable late fee increases to 64% if one incurred at least one late fee in the previous year, and the probability increases to 92% if the consumer ranked in the top decile based on avoidable fees in the previous year.

In the last part of this section, I document that these simple financial mistakes correlate with more complex – and more expensive – financial decisions, such as lack of account optimization, non-participation in stock markets, and lack of mortgage refinancing. This finding suggests that the latter more costly decisions are also distorted by optimization failures.

Combined, these results act as validity tests in favor of the notion that avoidable fees are a good proxy for poor financial decisions.

3.1 Measure of financial mistakes

An overdraft fee is a fee that is levied when a withdrawal exceeds the available balance. If the consumer makes a purchase using a debit card that is linked to an account with insufficient funds, an overdraft fee is levied on the account.[14] A late fee is a fee levied on credit card delinquency (i.e., failure to pay at least the minimum balance on the due date). I follow Scholnick, Massoud and Saunders (2013), and classify a fee as an avoidable fee if the consumer incurred the fee while simultaneous holding sufficient liquidity to meet either the purchase or minimum balance, respectively. In the case of an overdraft fee, I classify an overdraft fee as an avoidable fee if.

$$\text{Expenditure} \quad < \quad \text{Balances on deposit accounts} + \text{Card liquidity} - 1 \text{ month spending} \quad (3.1)$$

And I classify a late fee as avoidable if,

$$\text{Minimum Payment Due} \quad < \quad \text{Balances on deposit accounts} - 1 \text{ month spending} \quad (3.2)$$

where one-month spending is estimated as the average monthly outflow. Note the right-hand side of equation 3.1 includes liquidity broadly defined, that is, both account deposits as well as available unused credit limits on different cards, whereas the right-hand side of equation 3.2 only includes account deposits. Scholnick, Massoud and Saunders (2013) identify two key reasons for subtracting precautionary balances: (1) consumers might fear being liquidity

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[14]In general, overdraft fees are ascribed to all deposit transaction with insufficient funds. However, in this paper, I only analyze overdraft fees occurring from debit card purchases. That is, I am not classifying overdraft fees from other types of deposit account transfers as avoidable fees.

constrained in the future and/or (2) consumers are currently liquidity constrained.

The direct cost of incurring an overdraft fee is the overdraft fee itself:

$$\phi_{\text{overdraft}} = \text{overdraft fee.} \tag{3.3}$$

The late fee includes an additional term. As described in Table A1, some credit cards have an associated penalty APR. Conditional on credit card delinquency, the APR on the credit card increases to the penalty APR. Thus, the cost of not paying at least the minimum balance is

$$\phi_{\text{late}} = \text{late fee} + \Delta \text{APR} \times \text{Average Daily Balance.} \tag{3.4}$$

3.1.1 Results

In figure 1 I report the average annual costs of incurring avoidable late payment fees and overdraft fees. The average costs is calculated from 2012 to 2016 both inclusive. Customers are sorted by average yearly frequency of number of financial mistakes, and we see that a little less than one third of the population never incurred either an avoidable late fee or an avoidable overdraft fee in the five year period. Another third incurred less than one avoidable fee per year across the five years. The next 20% of the consumers incurred on average between one and three avoidable fees per year at an average yearly cost of around $75. The next 9% of the consumers incurred between three and six fees per year at an annual cost of $200. The next 4% incurred between 6 and 10 avoidable fees at a yearly cost of $350, and the last 5% of the consumers incurred more than 10 fees per year, i.e. more than 50 avoidable fees across the five year period. And the cost of these more than 50 avoidable fees were a yearly average of more than $950.

Combined, these results indicate that unambiguous are pervasive, more than two-thirds incur them, however the majority of the direct costs of financial mistakes are born by a smaller fraction of the population.

[Figure 1 about here.]

3.1.2 Demographic and financial characteristics

In table 1 I report demographic and financial characteristics of consumers sorted by the frequency of avoidable fees. The first column represents the 31% of consumers who in the period from 2012-2016 incurred neither an avoidable late payment fee nor an avoidable overdraft fee. The next four columns are sorted in quartiles by frequency of avoidable fees.

[Table 1 about here.]

We see that consumers with no fees are slightly older, but that there is no relationship across age conditional on a single mistake. Although there is no linear relationship with age, I do find a systematic non-linear relationship. Similar to Agarwal et al. (2009) I find a u-shaped life-cycle pattern across age. In figure 2 below I report the fitted value in a predictive regression of frequency of mistakes on age dummies and deciles of controls (income, credit score, and liquid assets), computing the intercept using the sample means for the controls. Agarwal et al. (2009) suggests that this u-shaped relationship reflects learning among the young and dementia or lower of IT literacy among the elderly[15].

[Figure 2 about here.]

There is a light variation across groups on annual income; the annual income of consumers with zero avoidable fees is $72k while the average annual income among the quartiles are between $73 and $63, falling in frequency of mistakes. There is however a significant variation across both total and liquid asset holdings. Both total and liquid assets increase from $148k and $7k to $367k and $24k respectively when comparing consumers with the most amount of avoidable fees with those without any. Credit card limit utilization increases in frequency of fees, while debt-to-income ratios are fairly stable. The percentage of consumers who have an online or mobile account is increasing in frequency of avoidable fees, and so are median monthly logins (conditional on having an account).

It is worth noting that although income does not seem to vary across the financial mistakes bin, total assets do. This suggests that our measure of financial mistakes proxies for behavior which leads to consumption inequality beyond income inequality (Campbell, 2016). For example, as consumers who make financial mistakes also have a lower savings-rate, their accumulated lifetime wealth is lower than the consumers who rarely make financial mistakes. This suggests that improving financial literacy could have significant effects on wealth inequality, a point raised by Lusardi and Mitchell (2007a).

3.2   Validity of measure

In the previous section I outlined the data and measured the frequency of avoidable overdraft fees and avoidable late fees. I this section I outline a number of validity tests. The purpose of the tests is to assess to what extend the avoidable card fees are a good measure of financial ignorance. I analyze to what extent the frequency of these avoidable overdraft fees and late payment fees is a valid measure of financial mistakes. The purpose is to test to what extent avoidable fees are indeed financial mistakes.

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[15]I thank Virginia Traweek for drawing my attention to anosognosia, the phenomenon in which seniors who have dementia tend to not fully recognize the extent of their impairment.

3.2.1 Calculating the implied discount rate

I estimate the implicit discount rate which the consumers are paying. If consumers are perfectly rational, they will only pay the avoidable fees, if they value their liquidity at at least that discount rate. I follow the standard methodology for calculating annual percentage rate on consumer debt:

$$\text{APR} = \frac{\text{Interest Charges}}{\text{Average Daily Balance}} \times \frac{365}{\text{Days in Billing Cycle}} \tag{3.5}$$

And equivalently for the overdraft mistake and the late payment mistake respectively I calculate:

$$\text{Implied discount rate} = \frac{\text{Cost of ODM}}{\text{Expenditure}} \times \frac{365}{\text{Days in Billing Cycle}} \tag{3.6}$$

$$\text{Implied discount rate} = \frac{\text{Cost of LPM}}{\text{Minimum balance}} \times \frac{365}{\text{Days in Billing Cycle}} \tag{3.7}$$

In figure 3 I report histograms of the implied discount rates for the two mistakes.

[Figure 3 about here.]

The distribution of implied monthly discount rates for the overdraft mistake range from almost 0% (when the purchase is very large relative to the fee) to more than 700% (when the purchase is small relative to the fee). The range of implied monthly discount rates for the late payment mistakes start at 100% as the late fee is almost always larger than the minimum payment itself.

As an illustrative example consider a consumer who has an outstanding balance of $1,000, with a minimum payment due of $25. Regular APR=18%, Penalty APR=29.99%, and Late Fee=$35. He considers the following two options: a) Only pay the minimum balance of $25, and thus borrow $975 for one month, and b) Not pay anything: borrow $1,000 for one month. The cost of these two options after one month are as follows: a) Total Finance Charge = 18%/12*$975 = $14.63. b) Total Finance Charge = 29.99%/12*$1,035 + $35 = $60.87. We see that the consumer will pay an additional $46 just to avoid paying the minimum payment of $25. That is equal to an implied a one-month interest rate of 185% (which is in line with the histogram of implied discount rates, see figure 3.

In order for a model with rational expectations to accurately describe these financial mistakes, the model must have preference parameters that allow the agent to pay monthly discount rates of above 100%.

3.2.2 Persistence of financial mistakes

In this section I analyze to what extend incurring an avoidable credit or debit card fee is randomly distributed across individuals, or to what extend it is a persistent characteristic of the consumer.

In the first step of this analysis, I run a linear predictive regressions, predicting whether consumer i will make at least a financial mistake of type j over the next 12 months, as a linear function on both a dummy indicating whether the consumer made a mistake in the prior 12 months as well as on the number of prior mistakes at time t and a non-parametric function of controls:

$$\mathbb{1}_{\{\text{mistake}_{i,t\to t+11}\}} = \beta \times \mathbb{1}_{\{\text{mistake}_{i,t-12\to t-1}\}} + f(\text{controls}_{it}) + \epsilon_{it} \tag{3.8}$$

$$\mathbb{1}_{\{\text{mistake}_{i,j,t\to t+12}\}} = \beta \times \text{mistake}_{i,j,t} + f(\text{characteristics}_{it}) + \epsilon_{it} \tag{3.9}$$

The regression coefficients are reported in 3. The conditional probability of incurring an avoidable late fee over the next 12 months increase from 10% to more than 32% if the consumer had incurred an avoidable late fee in the prior 12 months. Equivalently we see from regression 3.9 that for every avoidable late fee in the past 12 months, the probability increases with 12%-points for the following 12 months period. Equivalently, previous avoidable overdraft fees has a positive impact on the probability of future overdraft fees, a change in 15%-points for the dummy and 8% in the linear regression. The cross-correlations, regressing future late fees on past overdraft fees and vice versa, also have positive and statistically significant coefficients, albeit the economic magnitudes are slightly smaller.

As a second step in this analysis, I estimate a linear probability regressions where the dependent variable is the presence of a financial mistake by consumer i in month t:

$$\mathbb{1}_{\{\text{mistake}_{it}\}} = f(\text{characteristics}_{it}) + \mu_i + \epsilon_{it} \tag{3.10}$$

I use decile bins to non-parametrically control for: "Age", "Income", "Liquid assets", "Total assets", "Expenditure volatility", "credit score", "Debt-to-income", "Online account", and "Number of logins". As goodness-of-fit measures I calculate adjusted R^2, the square root of the mean squared error (RMSE), the mean absolute error (MAE), and the Pearson Correlation. Table 3 reports the results. We see that the explained variation increases by including a person fixed effect, and that effect appears across all four measures of goodness-of-fit increase: Adjusted R^2 and the Person Correlation increase, and the RMSE and MAE decrease.

[Table 2 about here.]

We can see the same result from a simple variance decomposition. I calculate the fraction

of the variance of the dependent variable which can be explained by a personal fixed effect:

$$\text{Var}(Y) = \underbrace{\text{Var}\left(\text{E}\left[Y|X\right]\right)}_{\text{Explained/between group variance}} + \underbrace{\text{E}\left[\text{Var}\left(Y|X\right)\right]}_{\text{Unexplained/within group variance}}$$

In appendix table A2 I calculate the variance decomposition the frequency and cost of the late payment mistake and the overdraft mistake. And the *explained variance* is $\text{Var}\left(\text{E}\left[Y|X\right]\right)/\text{Var}(Y)$. I find that price variation between the consumers explain between 25% and 35% of the variation. Given the unconditional probability, if the mistakes were distributed randomly, then a variance decomposition would should that the variation between customers would only explain between 2% and 3% of the variation. These results indicate that financial mistakes are not driven by random liquidity shocks. Instead, the data suggests that financial mistakes are driven by a persistent characteristic, in line with the behavioral view.

So far I have analyzed how much of the cross-sectional variation can be explained by a person fixed effect. In a second set of regressions, I look at the time-series dimension to analyze persistence across time. I regress a linear probability model of future mistakes at time $t + j$ conditional on making a mistake at time t. I interact the effect with the number of mistakes at t, to see how the conditional probability of future mistakes vary with the consumer's history of mistakes. Table 4 reports the regression coefficients. Consistent with the result in Agarwal et al. (2009) we see a short-term reversal in the probability of a mistake occurring. However this 'learning' effect almost completely dissipates when interacting with "repeat offenders". We see this as the coefficient on the interaction term larger and increasing.

[Table 3 about here.]

Lastly I calculate the transition probabilities across two two-year periods. I divide the sample into 2013-2014 and 2015-2016 and sort consumers by their quartile of financial mistakes within each two-year period. I then calculate the transition probability of moving from bin i to bin j, Pr_{ij}, as the fraction of consumers who were in bin i in 2013-2014 and in bin j in 2015-2016. Appendix table A3 reports the transition probabilities, and we see that a lot of the probability mass is centered on the diagonal.

3.2.3 Mistakes across multiple domains

In a second validity test, testing the validity of using avoidable fees as a proxy for financial ignorance, I compare the avoidable card fees with other standard financial mistakes, and I analyze if mistakes are correlated across domains. If the avoidable card fees that I measure are in fact financial mistakes caused by limited financial knowledge, then this would imply that consumers who incur frequent avoidable card fees also will exhibit similar behavior across other domains. In this section I measure four other types of financial mistakes and

calculate the cross-sectional correlation. The four mistakes include two account optimization mistakes, lack of mortgage refinancing and stock market non-participation.

Following Gathergood et al. (2017) and Ponce, Seira and Zamarripa (2017), I calculate the credit card payment mistake and the credit card spending mistake as follows: The optimal rule for allocating credit card payments is: (1) pay min. payment on all cards, then (2) pay highest APR card. If a consumer is not following this optimal rule, he incurs a cost of

$$\phi_{\text{payments}} = \left(r_{\text{high}} - r_{\text{low}}\right) * \min\left\{(smt_{\text{high}} - min_{\text{high}}), (pmt_{\text{low}} - min_{\text{low}})\right\} \qquad (3.11)$$

Similarly the optimal rule for allocating credit card expenditure is to allocate the expenditure on the card with the lowest effective APR, and a cost is incurred when: (finance charges on card i with spending) AND (card $j \neq i$ has unused credit and lower effective APR). The cost is measured as:

$$\phi_{\text{spending}} = \left(r_{\text{high}} - r_{\text{low}}\right) * \max\left\{c_{\text{high}}, limit_{\text{low}}\right\} \qquad (3.12)$$

While the above two optimization mistakes have relatively low costs for the consumer, there are examples in the literature of financial mistakes with much higher stakes. One particular example is the lack of mortgage refinance Andersen et al. (2015); Keys, Pope and Pope (2016); Agarwal, Ben-David and Yao (2017). Following this literature I define a "lack of mortgage refinancing" mistake by the following algorithm: credit score above 680, LTV below 90, and mortgage rate with the option to refinance above the average 30-year fixed rate + 0.5%-point.

Another "large-stake" financial mistake documented in the literature is "Stock Market Non-Participation" (Calvet, Campbell and Sodini, 2007; van Rooij, Lusardi and Alessie, 2011a; Klapper, Lusardi and Panos, 2013). I've merged the data on financial mistakes on credit and debit cards with data from investment accounts within the financial institution. And I calculate the cross-sectional correlation between the card mistakes and non-participation in investment accounts.

[Table 4 about here.]

In table 5 I report the cross-correlations between the two benchmark mistakes and the credit card payment, credit card spending mistake, failure to refinance a mortgage, and non-participation in investment accounts. Table 5 reports the correlation across bins of frequency of avoidable late fees and table 6 reports across bins of frequency of avoidable overdraft fees.

When we compare the group of consumers who have never incurred an avoidable late fee with the highest quartile, we see that the conditional probability of incurring an avoidable overdraft fee increases from 36% to 68%. Equivalently the probability of making a credit card

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spending mistake increases from 74% to 82%; the probability of making a credit card payment mistake increases from 54% to 66%; the probability of not refinancing your mortgage when it is optimal to do so increases from 87% to 93%; and the fraction of customers without an investment account increases from 92% to 98%.

Equivalently, comparing the group of consumers who have never incurred an avoidable overdraft fee with the highest quartile, we see that the conditional probability of incurring an avoidable late fee increases from 55% to 62%. The probability of making a credit card spending mistake increases from 73% to 81%; the probability of making a credit card payment mistake increases from 54% to 65%; the probability of not refinancing your mortgage when it is optimal to do so increases from 88% to 92%; and the fraction of customers without an investment account increases from 93% to 98%. In appendix table A5 I report the unconditional frequency of each of the four card mistakes.

3.3 Discussion

In the above section I measured the frequency of two benchmark financial "mistakes": paying a late fee while having sufficient liquidity available and paying an overdraft fee while having sufficient liquidity available. Both of these fees are avoidable, as sufficient liquidity is available on the on the due-day and the payment day respectively. And incurring both of these fees is a financial choice which differs from the simplest rational models.

I conducted a number of validity tests of avoidable fees as a measure of financial mistakes. First, I calculate the implicit discount rate paid by consumers who incur either the avoidable late fee or the avoidable overdraft fee. These were reported in figure 3, and we see that for the majority of the fees paid, the implicit monthly was higher than 100%, counter indeed to most rational models. In a second validity test I find that the avoidable card fees are highly persistent within an individual consumer, and in the last validity test I find that avoidable card fees correlate with other choices that the literature have associated with sub-optimal financial behavior, such as lack of between account optimization, lack of mortgage refinance, and lack of stock market participation.

4   Financial Mistakes and Consumption Smoothing

In the previous section I described the two benchmark financial mistakes, the avoidable credit card late fee and the avoidable debit card overdraft fee. I showed that these mistakes imply a high discount rate, persistent, and correlated with other mistakes. And I found suggestive evidence that they are caused by financial ignorance, rather than rational inattention.

In this section I investigate the effects of financial mistakes on consumption smoothing. In order to test the effect of financial mistakes on consumption smoothing I conduct an event-study. I study a subsample of consumers who have all taken a Home Equity Line of Credit

(HELOC). Payment for the HELOC is structured across two time periods. In the first period, the *draw period*, which typically lasts five or ten years, the consumer is only required to make interest payments. The interest rate is often floating and pegged to the prime rate. After the draw period the HELOC converts into a fully amortizing loan with a repayment period of between 10 and 20 years.

Figure A3 in the appendix outlines an example of a payout profile of a HELOC. In this example a hypothetical consumer has borrowed $50,000 using a HELOC. For the first 10 years the monthly payment during the draw period is $145.83, and thereafter the monthly payment increases to $494.43.

The sample of consumers who have a HELOC have incurred financial mistakes at approximately the same frequency as consumers in the full sample. We see this in 4 where I have plotted the frequency of consumers incurring either the late payment mistake, the overdraft mistake or both, sorted on average annual cost for the period November 2012 to June 2017, and we see that the distributions are very similar.

[Figure 4 about here.]

4.1 HELOC event-study: empirical specification

In this section I analyze the effect of financial mistakes on consumption fluctuations. The rational buffer-stock models will predict a zero change in consumption from a predictable negative, and I consider this the first null-hypothesis. In my first empirical test I calculate implied consumption by reset date for the entire sample:

$$Y_{it} = \alpha + \mu_i + \nu_{time} + \beta_t Reset_{it} + \Gamma X_{it} + \varepsilon_{it} \tag{4.1}$$

In figure I plot the fitted values of consumption relative to the reset date[16]. This figure plots months relative to the HELOC reset on the x-axis (date 1 is the first month after the end of the Draw Period), and the fitted value of total consumption expenditure on the y-axis. The expected consumption is around $1,900 per month and slightly decreasing towards the end of the draw period; directly after the draw period ends, the consumption falls with more than $50 and it continues to fall over the next 6 months. This pattern is inconsistent with a rational buffer-stock model.

[Figure 5 about here.]

Given the average result, I will test whether consumers who have a history of financial mistakes are more likely to cut their consumption following the HELOC reset. This test relates to a prediction from the survey literature on financial literacy: From the survey evidence

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[16]I use the methodology from Agarwal et al. (2013) to compute the intersect.

(e.g. Lusardi and Mitchell (2007*b*)) we see that consumers who display low levels of financial literacy also appear to be "bad planners". I.e. the consumers who answer incorrectly on questions regarding interest rates and compound interest also save less for retirement. I test whether this feature also is present in my data. I conduct this test using a subsample of consumers who have taken out interest-only Home Equity Lines of Credit (IO HELOCs). IO HELOCs have the particularly feature that for the first 5 or 10 years of the loan, the borrower only has to pay interest on the outstanding balance. This initial period is called the *draw period*. Following the draw period is a *repayment period*, often 20 to 25 years, over which the remainder of the loan is amortized.

This institutional setup means that borrowers of IO HELOCs faces a sharpe discontinuity in their monthly payments after the draw period. (See appendix figure A3 for an example.) Johnson and Sarama (2015) also use this discontinuity in payments, and they study default risk. They find that HELOCs have significantly higher default and payoff rates around the end of the draw period.

In order to test whether consumers who have a history of financial mistakes experience a higher MPC out of a predictable negative shock to income, I first sort consumers by their history of mistakes at the end of the draw period. The "control" group are the consumers who up until the reset data has never incurred any avoidable late or avoidable overdraft fees. This group accounts for approximately 30% of the sample. Among the remaining consumers, I sort the consumers in quartiles based on frequency of the two benchmark mistakes, and the "treatment" group is the highest quartile. In table 7 I report the mean value of Age, Income, Change in income over past six months, unemployment rate over past six months, internal credit score, total assets, liquid assets, and percentage of consumers who have an investment account. We see that for the variables on age and income the two groups are similar. However, for the remaining variables – those more related to financial choices – the two groups differ: The group who have made many mistakes have a lower (albeit still high) credit score. A significantly lower total assets and liquid assets, a higher debt-to-income, a higher credit card utilization rate and a lower frequency of investment accounts.

[Table 5 about here.]

To compare the differential consumption response to HELOC resets between the two groups, I run the following regression:

$$Y_{it} = \alpha + \mu_i + \nu_{time} + \beta_{jt}Reset_{jit} + \Gamma X_{it} + \varepsilon_{it} \qquad (4.2)$$

The dependent variable Y_{it} is total expenditure which is calculated as "credit card expenditure"+"debit card expenditure"+"account outflows"-"account outflows to pay for card debt". Notice that the last term is to ensure that card payments are not double counted. Also note

that t indexes months relative to the HELOC reset date – not calendar time. Instead ν_{time} is the calendar month fixed effect. The parameter α is a constant, μ_i is a consumer fixed effect. β_t is a vector of coefficients multiplying $Reset_{it}$, a set of monthly dummy variables for dates relative to HELOC reset. Γ is a matrix of coefficients multiplied on X_{it} which has deciles of the control variables mentioned above. I sort consumers by frequency of mistakes at HELOC-date=0, and then run regression 4.2 twice, once for the sample of consumers who have zero mistakes at HELOC-date=0, and once for the consumers in quartile 4, measure at HELOC-date=0.

I also run a difference-in-difference analysis to calculate change in consumption expenditure for the treatment group of different expenditure groups. I run the following regression:

$$Y_{it} = \alpha + \beta_1 \mathbf{1}_{\text{Loan age > reset date}_{it}} + \beta_2 \mathbf{1}_{\text{Ignorant}_i} + \beta_3 \mathbf{1}_{\text{Loan age > reset date}_{it}} \times \mathbf{1}_{\text{Ignorant}_i} + \varepsilon \quad (4.3)$$

The coefficient of interest the is coefficient on the interaction between the HELOC loan having reset and the treatment group of consumers. Below I report the coefficient for regressions where $t = 12$ months across a number of consumption categories.

4.2 HELOC Event-study: Results and robustness

Figure 6 plots the coefficients from β_t from regression 4.2. The two groups of consumers have pre-trends that are similar both in trend and at a level of approximately \$1,200 in credit card expenditure per month. Following the HELOC reset, the "control-group" (the group of consumers with no mistakes) experience no statistically significant change. The point estimate falls sightly, between \$0 and \$10 over the following 24 months, however this is within the standard errors of roughly \$50.

The treatment group, the consumers in the highest frequency-quartile of mistakes, on the other hand experience a significant decline in credit card expenditure. Following the HELOC reset, the fitted value of credit card expenditure for the the treatment group falls from around \$1,200 to around \$1,100, or almost 9%. We see that the decline is roughly linear from months 0 to month 21 and that it plateaus out from months 21 to month 24. This fall is significant at 5%-significance level.

[Figure 6 about here.]

We see that the point estimate on income is negative, however this fall is insignificant. The largest drops occurs in the categories of Travel (-\$27), Auto durables (-\$26), and Healthcare (-\$23). However, in the categories of Department Stores and Entertainment the point estimate is positive (\$19 and \$21 respectively), although statistically insignificant.

As a robustness exercise, I follow the methodology in Mian and Sufi (2012) and conduct a placebo analysis where I sort consumers at different HELOC-dates and plot the difference between the credit expenditure of the two groups. I have plotted the coefficients from three different placebo starting dates in appendix figure A3, and we see that the consumption drop following the HELOC reset is significantly outside the band of other placebo tests.

4.3 Discussion

A large previous empirical literature has studied the effect of borrowing constraints on consumer MPCs using predictable and positive changes to disposable income (Parker, 1999, 2015; Souleles, 1999; Johnson, Parker and Souleles, 2006; Stephens, 2006, 2008; Di Maggio et al., n.d.). This paper runs a similar event-study that compares the MPC out of predictable income changes across different groups of consumers. However, while the previous literature has studied predictable *positive* changes in disposable income, this paper studies a predictable *negative* change in disposable income. This seemingly innocuous difference allows for a sharply different interpretation.[17]

[Figure 7 about here.]

Figure 7 above represents a graphic explanation of this logic: With a predictable positive increase in disposable income the regression can distinguish between the consumption response from an unconstrained LC/PIH model from the consumption response of a constrained household. However, with a positive change the regression cannot distinguish between the consumption response of rational model and an ignorant model.

With a predictable *negative* change, the regression allows the econometrician to distinguish between a borrowing-constrained and *rational* agent from that of an *ignorant* agent. See figure 8 below.

[Figure 8 about here.]

5 Mechanisms and Magnitudes

In the previous sections we found that financial mistakes are prevalent, and that consumers who often make financial mistakes on average smooth their consumption less across a predictable negative change in disposable income. We have hypothesized that this relationship is driven by heterogeneity in consumer's ability to make financial decisions. In this section I discuss and test potential alternative mechanisms.

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[17]Other recent research that study the MPC from negative changes in income include Ganong and Noel (2016) who study consumption around the expiration of unemployment benefits. They also find a negative consumption response, counter to rational models. Baker and Yannelis (2017) and Gelman et al. (2015) examine the spending response to an unanticipated, temporary loss of income: the federal government shutdown.

5.1 Are consumers busy?

One potential alternative mechanism is that consumers who pay avoidable card fees are simply too busy. It is time consuming to pay your credit card bill on time and being up to date with which card that has sufficient funds, and potentially some consumers just value their time higher than the cost of the fee. I will test this alternative theory by looking at proxies for the cost of time and compare those with measures of the level of education. The first proxy for the value of time is whether or not the consumers has access to an online account with the bank. I find that among consumers who never have never incurred an avoidable card fee 88% has an online account and 58% has a mobile account. Whereas among the quartile of consumers who have incurred the most avoidable fees, 92% have an online account and 70% has a mobile. Additionally, the median number of logins is higher for the group of consumers who make many mistakes, 18 online and 12 mobile, versus a median of 13 online and 6 mobile logins for the group of consumers who never make mistakes. One potential confounding effect is that older people on average tend to be less tech savy which could drive this effect. However, I find that even after controlling for age fixed effects, consumers who have an online account are 0.7% more likely to make a monthly mistake than consumers without one. We see this in table 8, where I report the regression coefficients of linear regressions of mistake frequency on a dummy variable taking the value one if the consumer has an online account. In the regression I control for income and have age and month fixed effects. The same result appears if we regress mistake frequency on number of logins as well – see regression (2). After controlling for age and income, the effect of one additional monthly login increases the probability of a monthly mistake with .06.

[Table 6 about here.]

In a second set of regressions, I estimate how the frequency of mistakes varies with proxies for the level of education of the consumer. For every consumer I observe his or her ZIP code which I merge with data from the Census Bureau on average educational attainment in each ZIP code. For every consumer I calculate the fraction of households in her ZIP code that have obtained at least a high school degree, at least a 2 year college degree, and at least a 4 year college degree. I then regress the mistake frequency on these fractions and report the regression coefficients in regressions (3), (4), and (5), controlling for income and age. We see that the regression coefficients for all three measures are negative. A one percent increase in the fraction of households who have attained at least a high school degree is related to a 9.6%-point decrease in the probability of a monthly mistake. Note that the unconditional probability of a monthly mistake is 11%. The regression coefficient on the fraction of households with at least 2 year and 4 year college degrees are -8.5% and -8.3% respectively.

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Taken together, these results indicate that the frequency of avoidable card mistakes are more likely to be driven by lack of financial knowledge as opposed to the opportunity cost of time. Guided by these results I build a model where consumers make financial mistakes because they ignore features of the financial contracts, and I call this friction 'financial ignorance'.

5.2 A model of financial ignorance

In this section I augment a consumer-savings model with a cost of financial ignorance. I model financial ignorance as a cognitive cost of computing expectations of future financial payments, and, following Gabaix (2014), I assign the parameter κ as the cognitive cost.

Consider a standard consumption-savings model (Deaton, 1991; Aiyagari, 1994; Carroll, 1997) where a a representative household lives for $J + 1$ periods and derives utility from a composite good:

$$\mathbb{E}_0 \left[\sum_{t=0}^{J} \beta^t \frac{\mathbf{C}_t^{1-1/\sigma}}{1 - 1/\sigma} + \beta^J v(\cdot) \right] \tag{5.1}$$

with

$$\mathbf{C}_t = \left((1 - \phi)(n_t - \underline{n})^{\frac{\varepsilon-1}{\varepsilon}} + \phi l_t^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{5.2}$$

where n is a non-durable necessity goods, $\underline{n}$ is a subsistence level of necessity consumption, l is a non-durable luxury good, and $v(\cdot)$ represents a bequest motive. The parameter ϕ represents the relative taste for luxuries, σ is intertemporal elasticity of substitution, and ε is the intratemporal elasticity of substitution. The consumer is subject to a per period budget constraint where both the frequency of mistakes and his expectation of future consumer debt, a_{t+1}, depends on a financial ignorance parameter κ:

$$y_t + a_t - c_t - \psi(\kappa) = E_t \left[\frac{1}{1 + r^a} (\text{total assets})_{t+1} | \kappa \right] \tag{5.3}$$

The financial ignorance parameter κ biases expectation of future consumer debt, a_{t+1} towards zero. In the section below I will describe in detail how one can micro-found an expectations operator that generates this type of financial ignorance. The testable implication from this model is that consumers who pay avoidable fees more frequently will have a lower savings rate, i.e. they will choose a higher c_t for the same level of disposable income $y_t + a_t$.

For the asset and savings technoogy I follow Kaplan and Violante (2014) and assume that $\log y_t$ follow a discrete Markov process from $t = 0$ to $\tilde{J}$. The household has access to two types of assets; cash a_t and a HELOC b_t. Cash has a non-negativity constraint, $a_t \geq 0$, and

earns per period interest r^a. b_t is an interest-only T-year mortgage; the households pays an interest payment $r^b b$ for $\tilde{T}$ years, and then it amortizes the loan for remaining $T - \tilde{T}$ years.

Endowments and assets combined generate the following per period budget constraint for the houseold:

$$
y_t + a_t = \begin{cases} c_t + \frac{1}{1+r^a} a_{t+1} + r^b b & \text{if } 0 < t < \tilde{T} \\ c_t + \frac{1}{1+r^a} a_{t+1} + p^b & \text{if } \tilde{T} \leq t \leq T \end{cases}
\tag{5.4}
$$

With a coupon payment p^b which is valued at:

$$
p^b = b \left(r^b + \frac{r^b}{\left(1 + r^b\right)^{T-\tilde{T}} - 1} \right)
$$

Notice that this contract has a deterministic and discontinuous increase in payments at $\tilde{T}$ as $r^b b < p^b$, and the law of motion for the HELOC is defined as:

$$
b_{t+1} = \begin{cases} b_t & \text{if } 0 < t < \tilde{T} \\ b_t(1 + r^b) - p^b & \text{if } \tilde{T} \leq t \leq T \end{cases}
\tag{5.5}
$$

Now I solve the household's problem. Consider a household standing at time t. Define the discontinuous jump in debt payments as $x \equiv p^b - r^b b$. Then the present value of expected remaining lifetime resources at time t can be written as:

$$
\mathbb{E}_t \underbrace{\left[\sum_{t=t}^{\tilde{J}} \frac{y_t}{(1+r^a)^t} + \sum_{t=\tilde{J}+1}^{J} \frac{y^r + \psi y_{\tilde{J}}}{(1+r^a)^t} \,\middle|\, y_t \right] + a_t}_{\text{remaining lifetime income} \,=\, \omega} - \underbrace{\left(\sum_{t=t}^{\tilde{T}-1} \frac{r^b b}{(1+r^a)^t} + \sum_{t=\tilde{T}}^{T} \frac{p^b}{(1+r^a)^t} \right)}_{\text{remaining debt payments}}
$$

$$
= \omega_t - \left(\underbrace{\sum_{t=t}^{T} \frac{r^b b}{(1+r^a)^t}}_{\text{interest payments} \,=\, P_t} + \underbrace{\sum_{t=\tilde{T}}^{T} \frac{x}{(1+r^a)^t}}_{\text{principal payments} \,=\, \tilde{P}_t} \right) = \omega_t - P_t - \tilde{P}_t
$$

Now, consider a household which is financial ignorant. The household is lacks fianncial literacy in the sense that it is hard for the household to consider financial contracts, in particular contracts with effect far in the future. The purpose is to capture quaitatively the effect described in section 4.1. I capture this theoretically with the financial literacy parameter parameter κ. Following Gabaix (2014, 2016b) I define κ to penalize the household when it considers values of x different from zero. In appendix 6 I show how to solve this optimization

problem.

I calibrate the model, with a labor income process where log disposable income y_t follows the standard persistent process:

$$y_t = \rho y_{t-1} + \epsilon_t \qquad \text{where} \quad \epsilon_t \sim (0, \sigma^2) \tag{5.6}$$

and the consumer transitions between employment and unemployment with job finding and seperation rates, π_f and π_s respectively. When unemployed, the consumer receives unemployment benefit ν.

I analyze the model by numerical simulations, and I describe the consumption policy function in steady state. The consumption policy functions is calculated by iterating the Euler equation, using the endogenous gridpoints method of Carroll (2006) and described by Guerrieri and Lorenzoni (2015). I calibrate the model parameters for which there exists reliable evidence on (e.g. interest rate, borrowing limit, unemployment process) using external data, and use the dataset on avoidable fees to calibrate the cost of financial ignorance. I calibrate the model to hit the consumption drop in necessity goods. See figure 9.

[Figure 9 about here.]

In order to assess the welfare losses from financial ignorance, I run a numerical simulation of the model. I run a monte-carlo simulation of 10,000 draws from the parameter distributions and simulate the consumption paths. Section 10.2.2 of Gabaix (2016b) implies that the equation for optimal attention m given cognitive cost κ is:

$$m^* = \arg \min_{m \in [0.1]} \frac{1}{2} \Lambda (1 - m)^2 + \kappa m \tag{5.7}$$

For every simulation draw I follow the following procedure (outlined in Ganong and Noel (2016)) to solve for the optimal attention to the HELOC reset given a κ. See appendix C for a detailed description of the numerical procedure.

For every draw I calculate the consumption response for $\kappa = 0$ and for $\kappa = 5\%$, and I calculate the certainty equivalent net present value between the two. For the median household the value of this is $130 per year, and for the 90th percentile, it's valued at $1,740 per year, which is equivalent to 8% of median annual non-durable consumption

5.3 Discussion

As discussed in section 4, the standard rational buffer-stock models were not able to fit the consumption drop at the predictable decrease in disposable income at HELOC reset. I then evaluated the model of rational inattention (Sims, 2003; Reis, 2006), however I did not

find reduced form evidence in favor of this class of models from data on online and mobile login frequency.

The model of financial ignorance from Gabaix (2016*b*) does a better job of fitting the consumption pattern. A structural model is able to reproduce the consumption pattern, and additional testable implications could not be rejected through reduced form evidence from luxury spending. I estimate the cognitive cost κ to be just above 5% for the highest quartile of the population. Given these results I build and calibrate a structural model of financial ignorance and simulate 10,000 consumer paths. From this monte-carlo simulation I estimate that the certain equivalent of reducing κ from 5% to 0% would benefit consumers to an equivalent magnitude of 4% of lifetime income.

An additional testable implication of the model of financial ignorance is that a higher frequency of financial mistakes is associated with a higher expenditure ratio of luxury to necessity. The expectation of future payments are always biased downwards for ignorant consumers, and an implication is thus that they believe that they are wealthier than they really are, as they believe that their future liabilities are lower. A consumer who believes that he is wealthier than he is will not only have a higher expenditure, from consumer theory we know that he will move up further on the Engel Curve. That is, a consumer who believes that he is wealthier will have a higher expenditure share on luxury goods.

[Figure 10 about here.]

I define luxury goods as entertainment, electronics, jewelry and arts, and travel, and calculate the average expenditure share out of total expenditure for each consumer. I then plot a bin-scatter plot of 30 equal sized bins based on wealth, which we see in figure 10. Additionally I run a local-linear regression on the entire dataset. I conduct this exercise for two groups of consumers: consumers who have never incurred an avoidable card mistake, and for the group of consumers who have incurred the most mistakes. We see that at every level of wealth, the consumers who frequently make mistakes, have a higher expenditure share on luxury goods.

6   Conclusion

In this paper I investigate the relationship between financial mistakes and consumers' ability to smooth their consumption, using anonymized data from a million U.S. consumers on both financial and consumption choices. I document that simple avoidable card fees are pervasive, persistent and costly, and that incurring avoidable fees is correlated with other common financial mistakes such as lower account optimization, lower participation in risky asset markets, and lower mortgage refinancing. The consumers that I study are relatively sophisticated, which suggests that the patterns documented in the paper are likely accentuated

in other parts of the credit distribution. My findings also raise the question whether the more complex financial decisions are genuinely the result of rational choice or are also distorted by optimization failures, as noted by Campbell (2016).

I document that consumers who frequently pay avoidable fees display a large consumption response to a predictable increase in mortgage payments from a HELOC reset. This drop is inconsistent with rational models of consumption smoothing. I compare alternative mechanism that link financial mistakes and lack of consumption smoothing, and I find that the evidence is more supportive of financial ignorance than rational information inattention. The individual financial mistakes studied in this paper are simple and avoidable, and this leaves scope for financial products that "nudge" consumers (Thaler and Sunstein, 2008) for example auto-payment system to avoid credit card fees. However, this paper finds that some consumers make financial mistakes across multiple domains where "easy fixes" can prove insufficient. This leads to an interesting set of constraints for policy makers designing financial regulation. They need to trade off the benefits of regulation to the consumers who make mistakes – taking into account that only some aspects of such consumers might be impacted – with the costs of regulation to other financial market participants. This is an area of fruitful future research.

While I study the consumption responses over a horizon of five years, given the data limitations, what the effects of financial mistakes and financial illiteracy are over a longer horizon remains an open question. Studying this would help illuminate whether and how financial behavior impacts consumption over the entire life-cycle. Additionally, exploring the empirical finding that financial mistakes are correlated with higher expenditure on luxury goods further, could help illuminate the psychological mechanisms underpinning financial mistakes. I plan to pursue these in future research.

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Zeldes, Stephen P. 1989. "Consumption and Liquidity Constraints: An Empirical Investigation." *Source Journal of Political Economy*, 97(2): 305–346. 2, 4, 7

Figure 1: Financial Mistakes - Yearly Costs
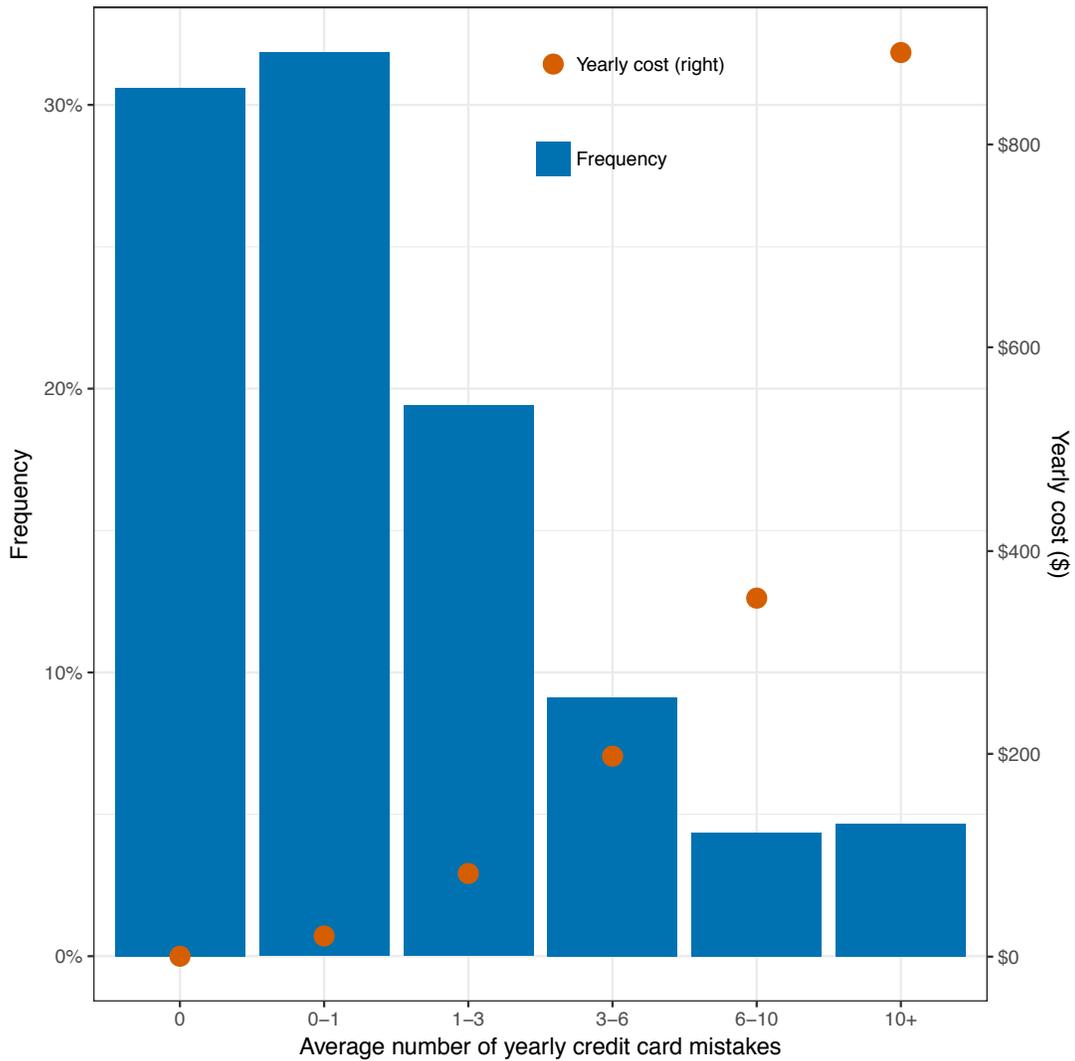
Note: This figure reports yearly frequency and costs of Late-payment-mistakes (LPM) and Overdraft-payment-mistakes (ODM) over the period 2012 to 2016 both inclusive. The bars are sorted by average yearly frequency, e.g. the fourth bar represents the 10% of consumers who have incurred on average between 3 and 6 LPMs and ODMs per year combined between 2012 and 2016, and the average yearly cost for this group is $200.

Figure 2: Financial Mistakes - By Age
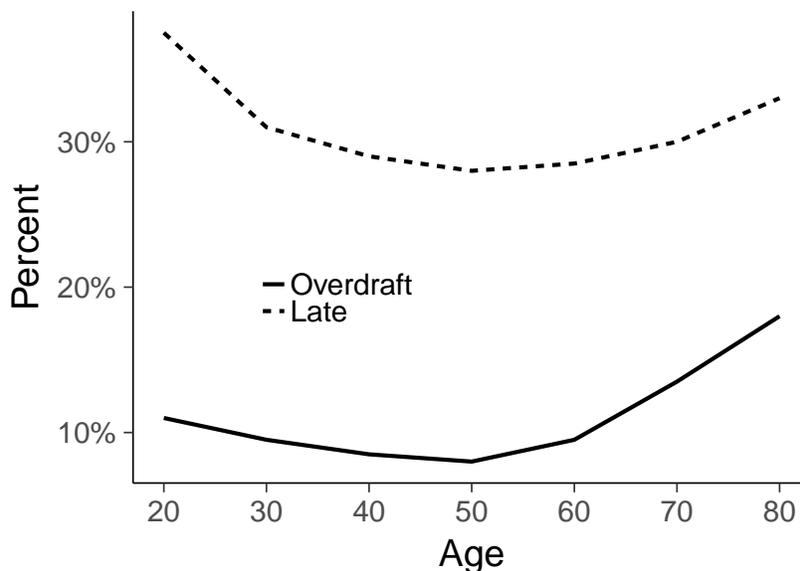
Note: Note: This figure reports the fitted value in a predictive regression of frequency of mistakes on age dummies and deciles of controls (income, credit score, and liquid assets), computing the intercept using the sample means for the controls. Sample is 1 million random sample. Period: Apr 2012 - Oct 2017.

Figure 3: Implied discount rates

(a) Overdraft Mistakes

(b) Late Payment Mistakes
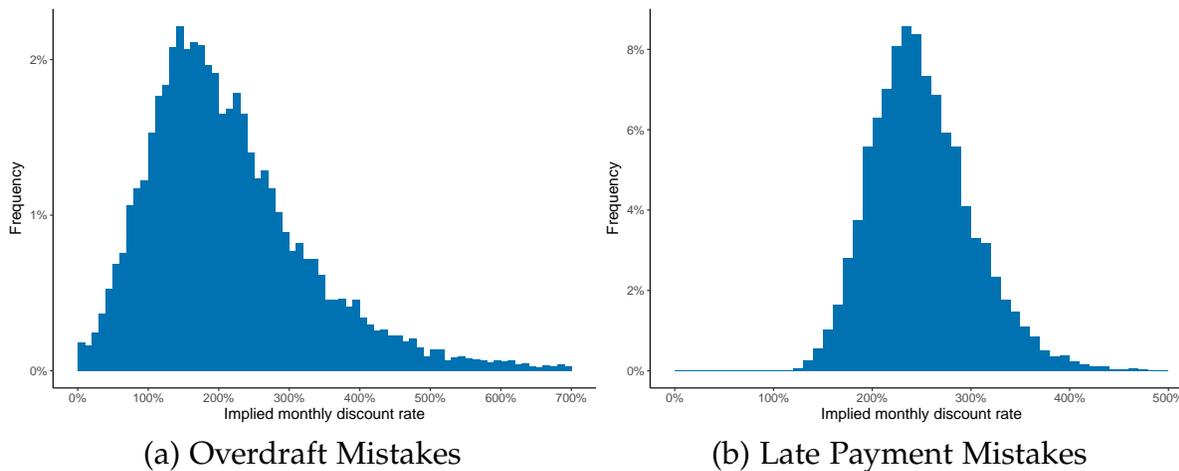
Note: The above figure reports the histogram over implied monthly discount rates for Overdraft Mistakes (ODM) and Late Payment Mistakes (LPM): Implied discount rate = $\frac{\text{Cost}}{\text{Expenditure}} \times \frac{365}{\text{Days in Billing Cycle}}$.

Figure 4: Mistake cost and frequency
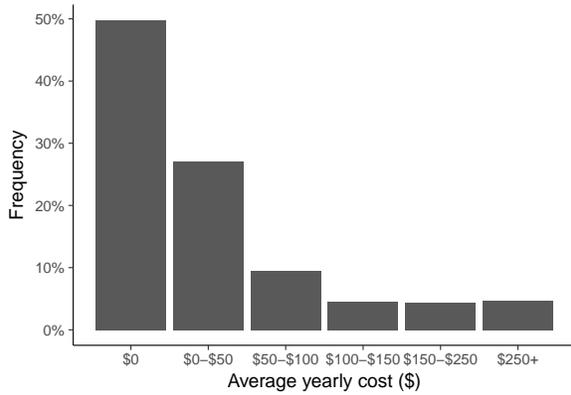
(a) Late Payment Mistake: Full sample
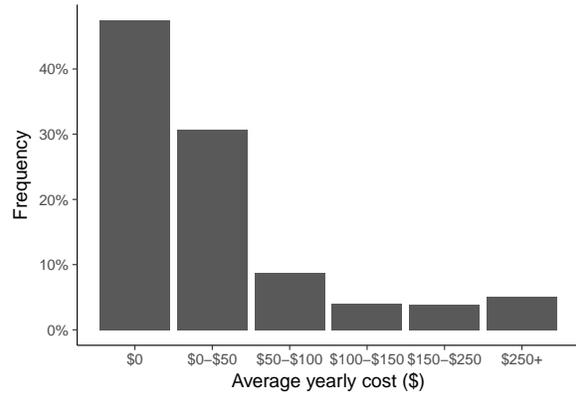
(b) Late Payment Mistake: HELOC sample
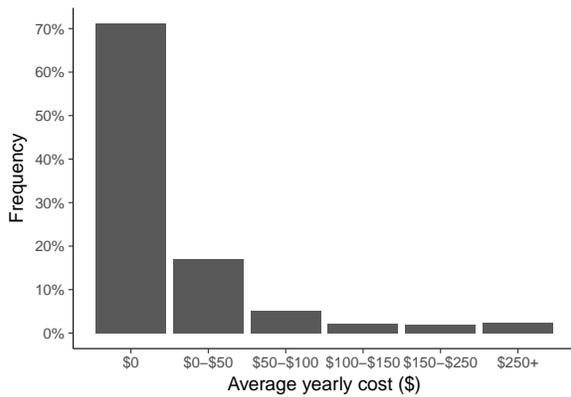
(c) Overdraft Mistake: Full sample
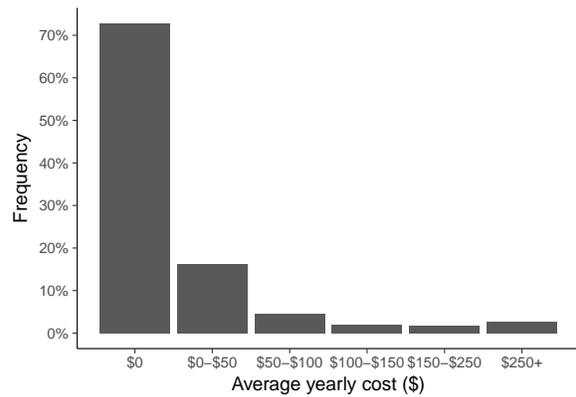
(d) Overdraft Mistake: HELOC sample
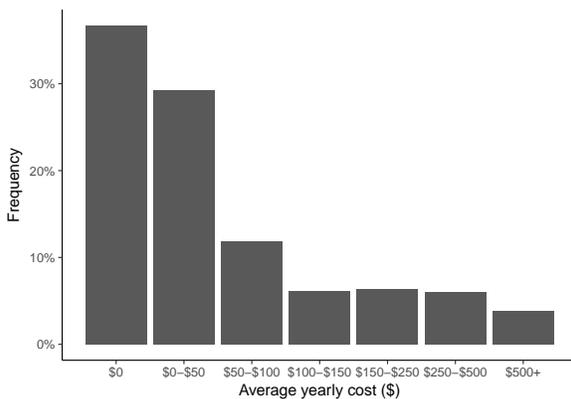
(e) Both mistakes: Full sample
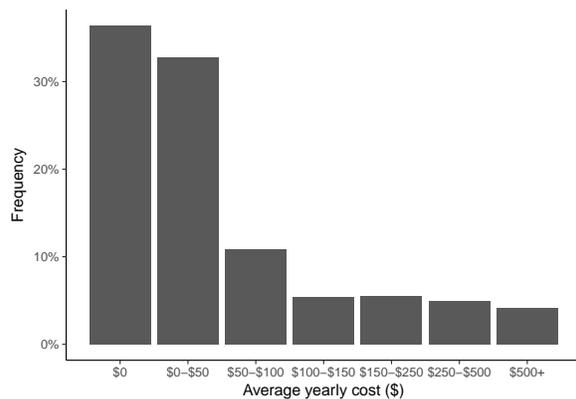
(f) Both mistakes: Heloc sample

Note: This figure plots the frequency of consumers by average annual cost of the financial mistakes for the period November 2012 to June 2017. Panels (a) and (b) report the frequency sorted by annual cost of the late payment mistake. Panels (c) and (d) sorted by the annual cost of the overdraft mistake. Panels (e) and (f) sorted on both mistakes combined. Panels (a), (c), and (e) report frequencies for the full sample, and panels (b), (d), and (f) report for the HELOC sample.

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Figure 5: Consumption expenditure and HELOC resets
– Full Sample
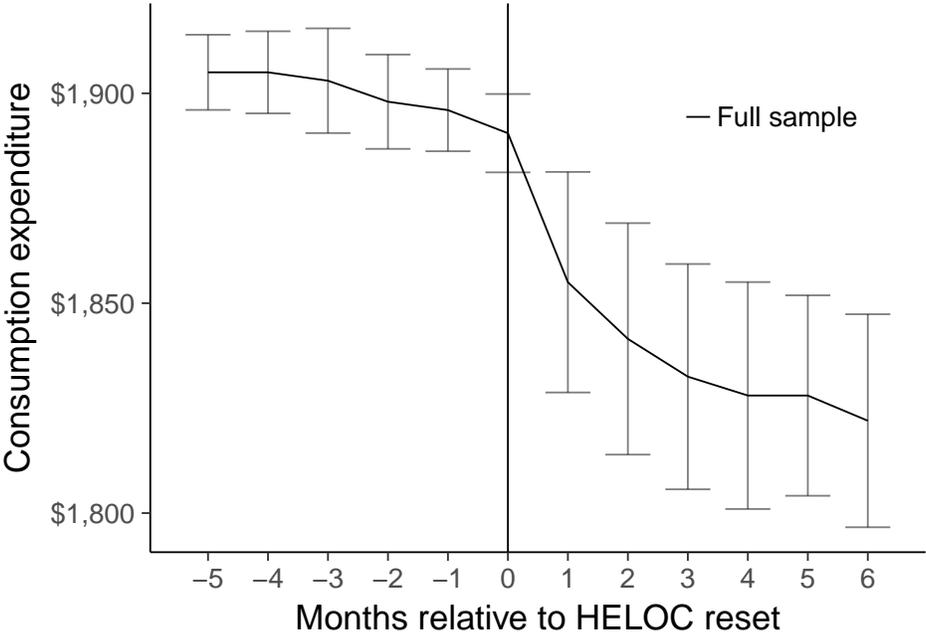
Note: This figure plots the fitted value of a regression of total consumption expenditure on dummy variables for months relative to HELOC reset, a constant, person- and calendar-time fixed effects, and decile bins of control variables (income, age, total assets, liquid assets, credit score, and consumption volatility from t=-5 to t=0).

Figure 6: Consumption expenditure and HELOC resets
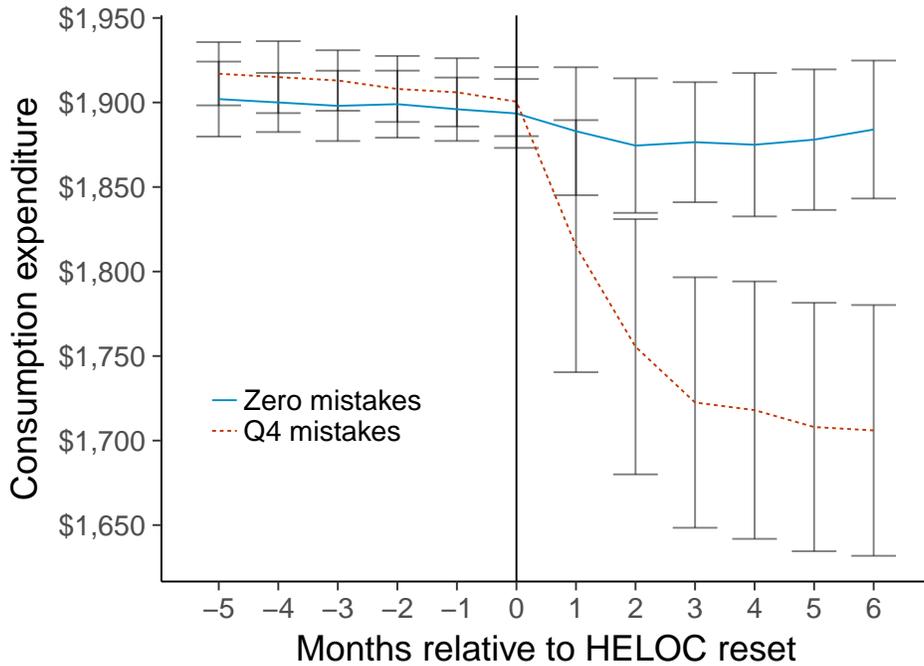
Note: This figure plots the fitted value of a regression of total consumption expenditure on dummy variables for months relative to HELOC reset, a constant, person- and calendar-time fixed effects, and decile bins of control variables (income, age, total assets, liquid assets, credit score, and consumption volatility from t=-5 to t=0).

Figure 7: MPC from predictable positive income change
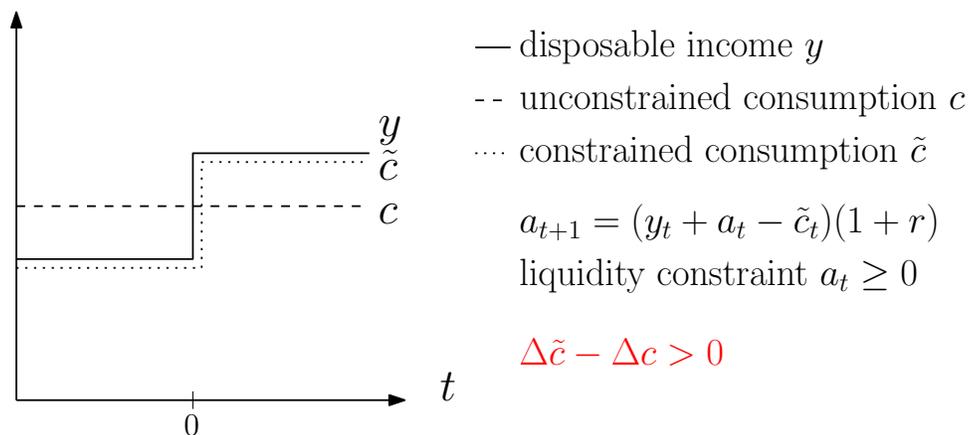
— disposable income y

- - unconstrained consumption c

···· constrained consumption $\tilde{c}$

$a_{t+1} = (y_t + a_t - \tilde{c}_t)(1+r)$

liquidity constraint $a_t \geq 0$

$\Delta\tilde{c} - \Delta c > 0$

Note: This figure plot the theoretical consumption response to a predictable increase in disposable income from an unconstrained and a borrowing constrained agent.

Figure 8: MPC from predictable negative income change
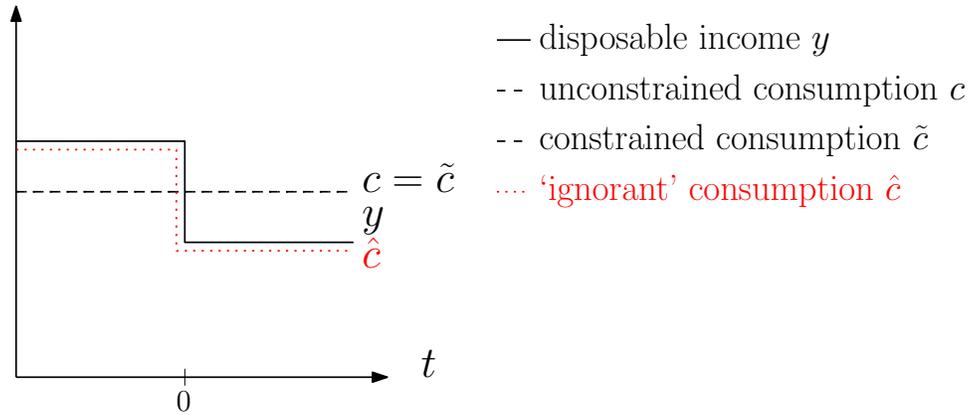
— disposable income y

-- unconstrained consumption c

-- constrained consumption $\tilde{c}$

···· 'ignorant' consumption $\hat{c}$

$c = \tilde{c}$

y

$\hat{c}$

Note: This figure plot the theoretical consumption response to a predictable increase in disposable income from an unconstrained, a borrowing constrained and rational agent, and from an ignorant agent.

Figure 9: Model calibration

(a) Overdraft Mistakes

(b) Late Payment Mistakes
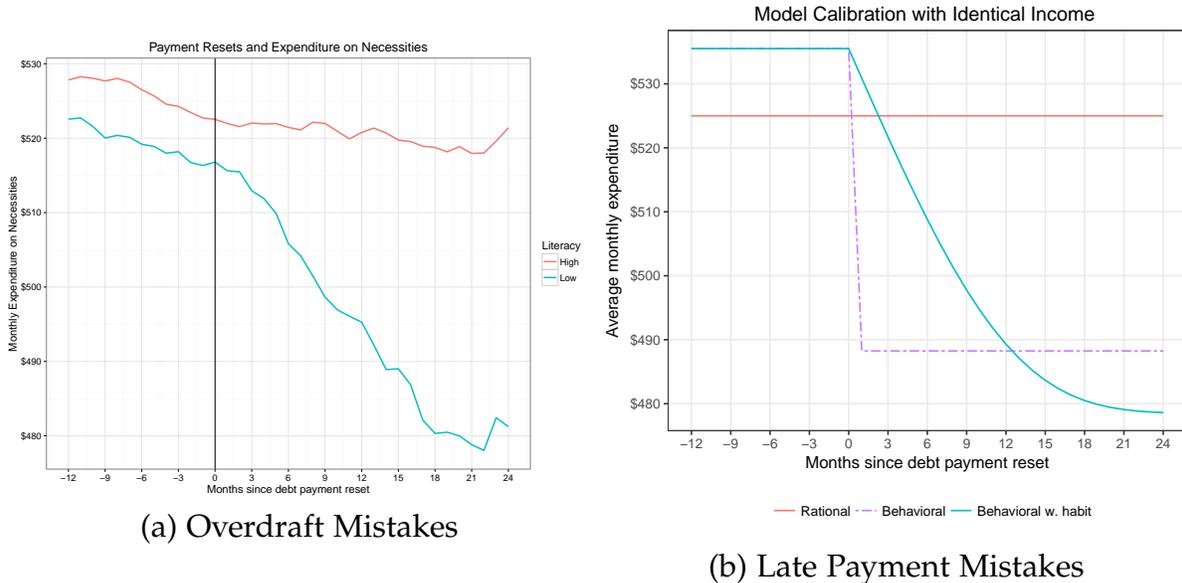
Note: The above figures plot necessity expenditure around HELOC reset date, and the corresponding calibration of the model. See section 4.1 for a description of the HELOC event study, and see table A7 for model parameters.

Figure 10: Financial Mistakes and Luxury Consumption
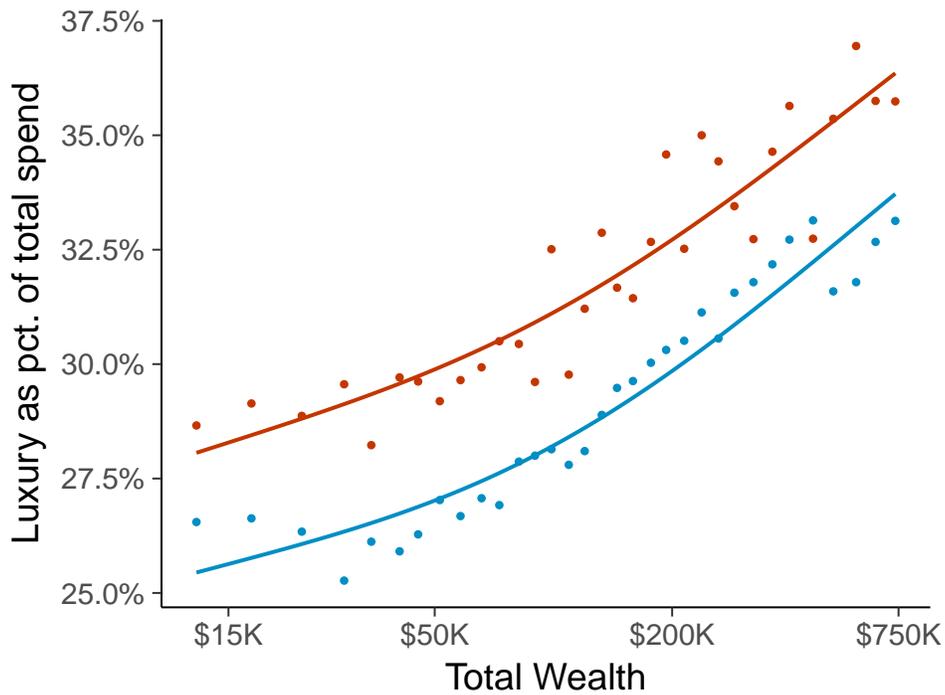
Note: This figure plot the average spending ratio on luxury goods relative to wealth for two groups of consumers: Consumers who never incurred avoidable card fees (in blue) and the quartile of consumers who most frequently have incurred avoidable fees (in red). Luxury goods are defined as: entertainment, electronics, jewelry and arts, and travel. The dots represent 30 equal sized bins based on wealth, and the solid line is a local-linear regression on the entire dataset.

Table 1: Characteristics of Customers - entire population

	Customers w. zero mistakes	Quartiles among positive values			
		Lowest	2Q	3Q	Highest
Age	47	47	45	44	42
Annual Income	$72,027	$72,607	$69,159	$66,623	$63,298
Liquid Assets	$24,401	$21,285	$16,337	$12,673	$6,868
Total Assets	$366,735	$315,267	$261,486	$210,532	$148,465
Credit Score	259	215	241	222	250
4 Year College	0.38	0.38	0.36	0.34	0.33

Table 2: Characteristics of Customers - HELOC sample

	Customers w. zero mistakes	Quartiles among positive values			
		Lowest	2Q	3Q	Highest
Age	57	57	58	57	55
Annual Income	$98,164	$99,207	$98,760	$99,270	$97,285
Liquid Assets	$33,408	$31,210	$28,507	$23,950	$14,603
Total Assets	$705,571	$647,178	$583,216	$495,489	$348,471
Credit Score	339	255	306	302	337
4 Year College	0.40	0.40	0.39	0.39	0.37

Note: The above two tables report mean values sorted by frequency of Late-payment-mistakes (LPM) and Overdraft-payment-mistakes (ODM) over the period 2012-2017. The first table is The first column represents the 31% of consumers who in the period have neither an LPM nor an ODM. The next four columns are sorted in quartiles by frequency of LPM and ODM.

Table 3: Linear probability models: Cross-sectional variation

	Dependent variable:					
	Late	Overdraft	Both	Late	Overdraft	Both
	(1)	(2)	(3)	(4)	(5)	(6)
Controls	Y	Y	Y	Y	Y	Y
Person FE	N	N	N	Y	Y	Y
Adjusted R^2	0.040	0.046	0.061	0.274	0.263	0.289
RMSE	0.283	0.142	0.300	0.239	0.121	0.253
MAE	0.161	0.041	0.180	0.116	0.031	0.130
Pearson Correlation	0.200	0.215	0.248	0.565	0.556	0.578
Observations	1,425,957	1,425,957	1,425,957	1,425,957	1,425,957	1,425,957

Note: This table reports goodness-of-fits for linear probability models of late payment mistakes (Late), overdraft mistakes (Overdraft) and both. The dependent variable is an indicator function taking the value 1 in months where a mistake occurs and 0 otherwise. The controls include decile bins of "Age", "Income", "Liquid assets", "Total assets", "Expenditure volatility", "credit score", "Debt-to-income", "Online account", and "Number of logins".

Table 4: Linear probability models: Cross-sectional variation

	Dependent variable:								
	Late			Overdraft			Both		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unconditional	0.08	0.08	0.08	0.04	0.04	0.04	0.10	0.10	0.10
$\mathbb{1}_{\{\text{mistake}_{it}\}}$	0.06	0.07	0.09	0.02	0.03	0.05	0.06	0.07	0.11
$\mathbb{1}_{\{\text{mistake}_{it}\}} \times \text{TWICE}$	0.08	0.09	0.12	0.02	0.04	0.07	0.08	0.10	0.14
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,425,957	1,183,810	791,761	1,425,957	1,183,810	791,761	1,425,957	1,183,810	791,761
Adjusted R^2	0.124	0.085	0.057	0.160	0.073	0.060	0.172	0.063	0.052

Note: This table presents coefficients from regressions relating the probability of a financial mistake at time $t + j$ to an occurrence of a financial mistake at time t. In columns (1), (4), and (7) $j = 1$, in columns (2), (5), and (8) $j = 3$, and columns (3), (6), and (9) $j = 9$. The first row reports the unconditional probability which is constant across time horizons. The dependent variable $\mathbb{1}_{\{\text{mistake}_{it}\}}$ is an indicator function taking the value 1 if a mistake occurs in month $t + j$ and 0 otherwise. The variable TWICE is and indicator function taking the value 1 if the cumulative number of mistakes for customer i at time t is greater than one, and zero otherwise.

Table 5: Correlation across multiple mistakes: Avoidable Late Fees

	Customers w. zero mistakes	Quartiles among positive values			
		Lowest	2Q	3Q	Highest
Avoidable overdraft fees	36%	51%	55%	61%	68%
CC spending mistake	74%	77%	76%	79%	82%
CC payment mistake	54%	60%	59%	62%	66%
Mortgage non-optimal	87%	91%	91%	90%	93%
Investment non-participation	92%	97%	97%	98%	98%

Table 6: Correlation across multiple mistakes: Avoidable Overdraft Fees

	Customers w. zero mistakes	Quartiles among positive values			
		Lowest	2Q	3Q	Highest
Avoidable late fees	55%	59%	60%	59%	62%
CC spending mistake	73%	76%	77%	80%	81%
CC payment mistake	54%	60%	59%	61%	65%
Mortgage non-optimal	88%	91%	91%	91%	92%
Investment non-participation	93%	96%	97%	97%	98%

Note: The above two tables report frequency of various financial mistakes sorted on frequency of avoidable late and overdraft fees. For avoidable late fees is reports the frequency of avoidable overdraft fees, credit card spending mistakes, credit card payment mistakes, lack of mortgage refinancing, and non-participation in investment accounts. For avoidable overdraft fees it reports avoidable late fees, credit card spending mistakes, credit card payment mistakes, lack of mortgage refinancing, and non-participation in investment accounts.

Table 7: Characteristics of Customers - Demographics and Income

	Customers w. zero mistakes (31% of sample)	Q4 by mistakes frequency (17% of sample)
Demographics and Income		
Age	58	55
Income	$98,164	$97,285
Δ Income in past 6 months	$792	$719
Unemployment in past 6 months	2%	2%
Financial Choices		
Credit Score	339	337
Total Assets	$705,871	$348,471
Liquid Assets	$32,008	$9,624
Investment Account	19%	5%

Note: This tables report the mean values for the HELOC sample of Age, Income, Change in income over past six months, unemployment rate over past six months, internal credit score, total assets, liquid assets, and percentage of consumers who have an investment account. The two groups of consumers compared are sorted by frequency of the two benchmark financial mistakes on the last month of their HELOC draw period.

Table 8: Consumer characteristics - Online access and education

		Dependent variable: Mistake Frequency				
	(1)	(2)	(3)	(4)	(5)	(6)
Online acct	0.696***					
	(0.095)					
Online logins		0.062***				0.059***
		(0.002)				(0.002)
High School			−9.623***			−8.535***
			(0.218)			(0.251)
2y College				−8.493***		
				(0.132)		
4y College					−8.266***	
					(0.129)	
Log(income)	−1.945***	−1.945***	−1.428***	−0.994***	−0.995***	−1.528***
	(0.039)	(0.045)	(0.040)	(0.041)	(0.041)	(0.047)
Age FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
State cluster	Y	Y	Y	Y	Y	Y
R^2	0.043	0.049	0.046	0.049	0.049	0.051
Observations	748,391	573,346	748,391	748,391	748,391	573,346

Note: This table reports regression coefficients from cross-sectional regression with the frequency of a benchmark financial mistake as the dependent variable. The benchmark mistakes are "avoidable late fee" and "avoidable overdraft fee", and the frequency is measured in percent. The unconditional frequency is 11%. Online acct is a dummy-variable indicating if the consumer has access to an online account. Online logins is the average number of monthly online logins. The education variables are from the Census Bureau. High School is the fraction of households in the ZIP-code with at least a high school degree. 2y College and 4y College are the fraction of households in the ZIP-code with at least a 2-year and 4-year college degree respectively.

Appendix A: Additional Figures and Tables

Figure A1: US aggregate Credit Card Fee and Interest Income
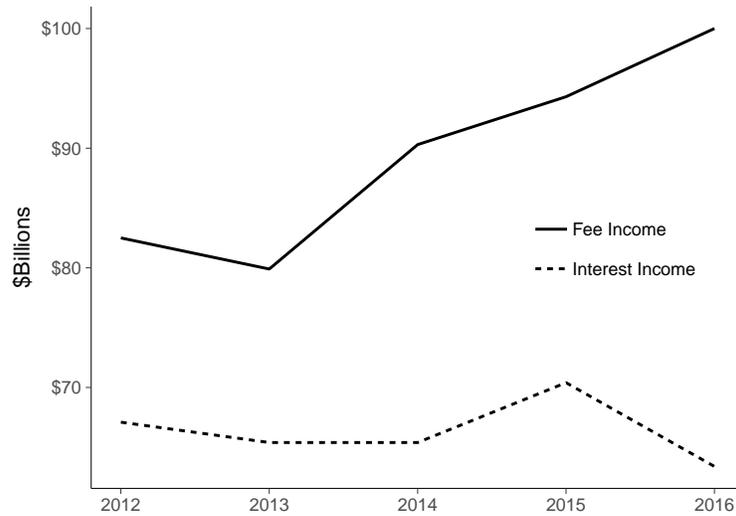
Note: This figure plots the aggregate income from credit card fees and from credit card interest income.
Source: Creditcards.com and R.K. Hammer Bank Card Advisory Report (7/23/2017).

Figure A2: IO HELOC example
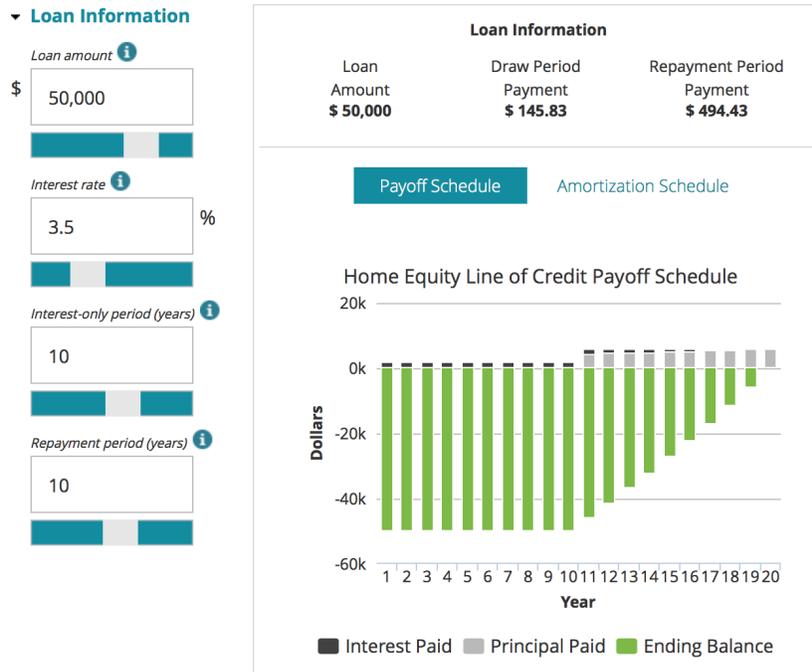
This figure plots an example of a payment schedule from an Interest Only Home Equity Line of Credit. Source: Creditcards.com (7/23/2017).

Figure A3: HELOC - Placebo tests
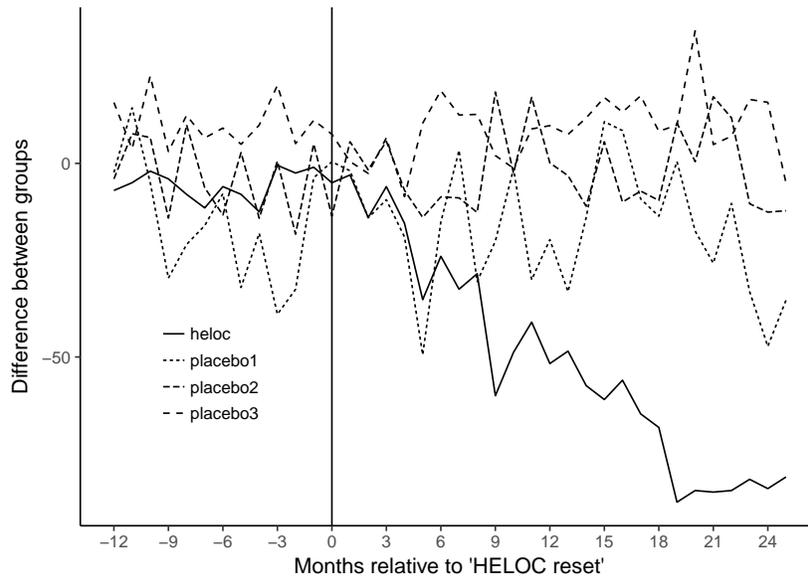
Note: This figure represents three placebo tests for the impact of HELOC reset on credit card expenditure. The solid line represents the difference in credit card expenditure in the around the true HELOC reset dates. Placebo1 has start-year=3, Placebo2 has start-year=6, and Placebo3 has start-year=15.

Table A1: Landscape of overdraft and late fees

	Overdraft Coverage Fees			Late Payment Fees		
	Fee (per item)	Max Fees per Day	Total Possible Cost in a Day	First late fee	Second late fee	Penalty APR
Bank of America	$35	4	$140	$27	$37	29.29%
Chase	$34	3	$102	$15/$27	$35	29.99%
Citibank	$34	4	$136	$0	$0	None
Wells Fargo	$35	4	$140	$27	$37	None
American Express				$26	$37	29.24%
Capital One				$25	$35	None
Discover				$0	$35	None

Source: Creditcards.com (4/12/2017) and Nerdwallet.com (4/12/2017).
Cards: Bank of America: Bank of America BankAmericard. No more than the total minimum payment due; if your balance is less than $100, you won't get a late fee. Chase: Chase Freedom. Up to $15 for balances under $100; up to $27 for larger balances. Citibank: Citi Simplicity. No late fees for the Citi Simplicity. Wells Fargo: Wells Fargo Rewards Visa. American Express: American Express BlueCash Everyday. Capital One: Capital One Quicksilver. Discover: Discover It. No fee for the first late payment.

Table A2: Variance Decomposition

	LPM frequency	ODM frequency	LPM cost	ODM cost
Total variance	0.08	0.02	1,005.82	302.95
Within	0.77	0.78	0.67	0.70
Between	0.25	0.24	0.35	0.32

Note: This table reports the variance decomposition of frequency and cost of late payment mistakes (LPM) and overdraft mistakes (ODM).

Table A3: Transition matrix - Late Payment Mistake

	Zero	Q1	Q2	Q3	Q4	Average cost	Frequency
Zero	0.78	0.10	0.07	0.04	0.02	0.00	0.53
Q1	0.58	0.17	0.14	0.08	0.03	25.24	0.12
Q2	0.43	0.16	0.19	0.16	0.06	61.93	0.12
Q3	0.28	0.10	0.18	0.27	0.18	157.95	0.12
Q4	0.14	0.03	0.08	0.20	0.55	871.08	0.12

Table A4: Financial Mistakes Frequency - HELOC sample

	Zero	Q1	Q2	Q3	Q4	Average cost	Frequency
Zero	0.92	0.03	0.03	0.01	0.01	0.00	0.86
Q1	0.62	0.13	0.13	0.06	0.05	33.84	0.04
Q2	0.52	0.14	0.15	0.09	0.10	80.45	0.03
Q3	0.38	0.14	0.16	0.13	0.19	163.15	0.03
Q4	0.18	0.07	0.12	0.13	0.50	764.22	0.04

Note: The above two tables report the transition matrices for the late payment mistake and the overdraft mistake. The transition probabilities are calculated between frequency bins calculated over two two-year periods, 2013-2014 and 2015-2016.

Table A5: Financial Mistakes Frequency - entire population

	Month w. zero	Customers w. zero	Share of fees avoidable (ew)	Share of fees avoidable (vw)
Avoidable late fee	0.92	0.42	0.94	0.92
Avdbl. overdraft	0.96	0.66	0.81	0.75
CC payment	0.64	0.40	0.46	0.01
CC spending	0.62	0.23	0.48	0.04

Table A6: Financial Mistakes Frequency - HELOC sample

	Month w. zero	Customers w. zero	Share of fees avoidable (ew)	Share of fees avoidable (vw)
Avoidable late fee	0.93	0.43	0.96	0.95
Avdbl. overdraft	0.97	0.72	0.78	0.73
CC payment	0.67	0.42	0.44	0.01
CC spending	0.62	0.23	0.52	0.04

Note: The above two tables report the frequency of four financial mistakes across the entire population and the HELOC sub sample respectively. The first column reports the fraction of months where no mistake is observed, and the second column reports the fraction of customers who never incur the respective mistake from 2012-2016. The third column is calculated as the fraction of months with avoidable mistakes relative to the number of months with a finance charge in the same category. The last column is calculated similarly to the third, but weighted by the dollar amount of the finance charge.

Table A7: Model calibration

Parameter	Definition	Value	Target/Source
β	Discount factor	$0.9^{\frac{1}{12}}$	See text
σ	Coefficient of relative risk aversion	$\frac{1}{2}$	Hall (2011)
ϵ	Intertemporal elasticity of substitution	1	Schmidt et al. (2017)
ϕ	Relative taste for luxuries	0.3	Mean luxury expenditure fraction
ρ	Persistence of income shock	0.95	See text.
σ^2	Variance of income shock	0.05	See text.
π_f	Job finding rate	0.08	Shimer (2005)
π_s	Job seperation rate	0.01	Shimer (2005)
ν	Unemployment benefit	0.4	40% of average labor income.

Note: All variables are calibrated monthly.

Table A8: Liquidity - OLS specification

	Log Total Liquid Assets at data $t+j$					
	Same month	1 month	3 months	6 months	9 months	12 months
LPM	−0.143***	−0.108***	−0.066***	−0.035***	−0.026***	−0.024***
	(0.007)	(0.007)	(0.005)	(0.004)	(0.004)	(0.005)
Controls	Y	Y	Y	Y	Y	Y
Person, month FE	Y	Y	Y	Y	Y	Y
Income bin clusters	Y	Y	Y	Y	Y	Y
Observations	2,144,909	2,090,294	1,982,798	1,825,704	1,673,571	1,526,201
Adjusted R^2 (full)	0.760	0.762	0.765	0.772	0.779	0.786
Adjusted R^2 (proj)	-0.024	-0.025	-0.027	-0.028	-0.0.30	-0.0.32

Note: This table presents coefficients from regressions relating liquid savings to late payment mistakes from the first 24 month after issuance of a credit card. The unit of observation is person times month. The dependent is measured in dollars. "LP Mistake" is an indicator function taking the value 1 in months where a late payment mistake occurs and 0 otherwise. Controls includes decile bins of income, age and credit score. *,**,*** Coefficient statistically different than zero at the 10%, 5%, and 1% confidence level, respectively.

Table A9: Liquidity - DID specification

	Log Total Liquid Assets at data $t+j$					
	Same month	1 month	3 months	6 months	9 months	12 months
LPM	-0.091^{***}	-0.067^{***}	-0.029^{***}	-0.026^{***}	-0.017^{*}	-0.023^{**}
	(0.011)	(0.009)	(0.011)	(0.009)	(0.010)	(0.009)
POST	-0.029^{***}	-0.025^{***}	-0.013^{**}	-0.001	-0.008	-0.010
	(0.007)	(0.006)	(0.005)	(0.007)	(0.010)	(0.012)
LPM $\times$ POST	-0.076^{***}	-0.050^{***}	-0.038^{***}	-0.002	-0.010	-0.012
	(0.012)	(0.013)	(0.012)	(0.013)	(0.008)	(0.012)
Person, month FE	Y	Y	Y	Y	Y	Y
Income bin clusters	Y	Y	Y	Y	Y	Y
Observations	2,144,909	2,090,294	1,982,798	1,825,704	1,673,571	1,526,201
Adjusted R^2 (full)	0.772	0.772	0.775	0.781	0.786	0.793
Adjusted R^2 (proj)	-0.024	-0.025	-0.027	-0.028	-0.0.30	-0.0.32

Note: This table presents coefficients from regressions relating liquid savings to late payment mistakes from the first 24 month after issuance of a credit card. The unit of observation is person-month. The dependent varialbe is measured in dollars. "LP Mistake" is an indicator function taking the value 1 in months where a late payment mistake occurs and 0 otherwise. POST is an indicator variable taking the value 1 in months 13-24 and 0 otherwise. $LPM is the measured cost of a late payment mistake. $^{*},^{**},^{***}$ Coefficient statistically different than zero at the 10%, 5%, and 1% confidence level, respectively.

Table A10: Liquidity - OLS in levels

	Log Total Liquid Assets at data $t+j$					
	Same month	1 month	3 months	6 months	9 months	12 months
$\widehat{\$LPM}$	-0.002^{***}	-0.002^{***}	-0.001^{***}	-0.001^{***}	-0.0005^{***}	-0.0004^{***}
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Person, month FE	Y	Y	Y	Y	Y	Y
Income bin clusters	Y	Y	Y	Y	Y	Y
Observations	2,144,909	2,090,294	1,982,798	1,825,704	1,673,571	1,526,201
Adjusted R^2 (full)	0.760	0.762	0.765	0.772	0.779	0.786
Adjusted R^2 (proj)	-0.024	-0.025	-0.027	-0.028	-0.0.30	-0.0.32

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A11: Liquidity - IV in levels

	Log Total Liquid Assets at data $t+j$					
	Same month	1 month	3 months	6 months	9 months	12 months
$\widehat{\$LPM}$	−0.002***	−0.001***	−0.001***	−0.0004***	−0.0003**	−0.0002**
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Person, month FE	Y	Y	Y	Y	Y	Y
Income bin clusters	Y	Y	Y	Y	Y	Y
Observations	791,761	772,884	735,222	679,730	626,343	575,001
Adjusted R^2 (full)	0.772	0.772	0.775	0.781	0.786	0.793
Adjusted R^2 (proj)	-0.024	-0.025	-0.027	-0.028	-0.0.30	-0.0.32

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix B: Test of causal effect on liquidity

In order to analyze the effect of an avoidable fee on liquidity I use a difference-in-difference research design. The DID design uses relies on the contractual discontinuity which means that the penalty APR is only levied after the first 12 months.

In this section I estimate the causual impact of paying an avoidable fee on a consumer's liquid assets. I use a difference-in-difference research design that explores an institutional feature of the cost of late payments: Recall that the Late Payment Mistake (LPM) occurs when a consumer fails to pay the minimum payment AND the consumer has sufficient deposits (over and above precautionary savings). When a consumer fails to pay the minimum balance, he is officially in *violation of the contract*, and two things occur: (1) He receives a late fee, and (2) the interest rate on the outstanding balance increases to the *penalty apr*. In appendix table A1 we see examples of penalty APRs. Penalty APRs are legally capped at 29.99% as per the CARD acct.

As an illustrative example consider a consumer who has an outstanding balance of $1,000, with a minimum payment due of $25. Regular APR=18%, Penalty APR=29.99%, and Late Fee=$35. He considers the following two options:

a) Only pay the minimum balance of $25, and thus borrow $975 for one month.

b) Not pay anything: borrow $1,000 for one month.

The cost of these two options after one month are as follows:

a) Total Finance Charge = 18%/12*$975 = $14.63

b) Total Finance Charge = 29.99%/12*$1,035 + $35 = $60.87

We see that the consumer will pay an additional $46 just to avoid paying the minimum payment of $25. That is equal to an implied a one-month interest rate of 185% (which is in line with the histogram of implied discount rates, see figure 3) .

Given this example, we want to ask: what is the causal impact of making a late payment mistake on end-of-month liquid assets. There is an obvious endogeneity concern: A customer makes the late payment mistake when he is not paying his credit card statement, which might correlate endogeneously with a negative liquidity shock. The solution is to use exogenous variation in the cost of the late payment mistake from the Penalty APR. The CARD act has enforced that in the first 12 months after opening a card, no Penalty APR can be imposed. This offers a natural difference-in-difference research design where I can compare mistakes made in the first 12 months with mistakes made in months 13-24. Of course the identifying assumption is that customers are similar on unobservables that would affect liquidity in months 1-12 vs. months 13-24.

Table A12: Liquid Savings and Late Payment Mistakes

| | *Dependent variable:* | | | | | |
| | End-of-month liquid savings | | | | Liquid savings after 3 months | |
	(1)	(2)	(3)	(4)	(5)	(6)
LP Mistake	−0.143***	−0.091***			−0.029***	
	(0.007)	(0.011)			(0.011)	
POST		−0.029***			−0.013***	
		(0.007)			(0.005)	
LP Mistake × POST		−0.076***			−0.038***	
		(0.012)			(0.012)	
$LPM			−0.002***	−0.002***		−0.001***
			(0.0001)	(0.0002)		(0.0002)
Specification	OLS	DID	OLS	IV	DID	IV
Person, month FE	Y	Y	Y	Y	Y	Y
Income bin clusters	Y	Y	Y	Y	Y	Y
Observations	2,144,909	791,761	791,761	791,761	791,761	791,761
Adjusted R^2 (full)	0.760	0.772	0.760	0.772	0.772	0.772
Adjusted R^2 (proj)	-0.024	-0.025	-0.027	-0.028	-0.027	-0.030

Note: This table presents coefficients from regressions relating liquid savings to late payment mistakes from the first 24 month after issuance of a credit card. The unit of observation is person-month. The dependent varialbe is measured in dollars. "LP Mistake" is an indicator function taking the value 1 in months where a late payment mistake occurs and 0 otherwise. POST is an indicator variable taking the value 1 in months 13-24 and 0 otherwise. $LPM is the measured cost of a late payment mistake. *,**,*** Coefficient statistically different than zero at the 10%, 5%, and 1% confidence level, respectively.

Table (A12) reports the results. Following the methodology of Agarwal et al. (2015*a*) and Agarwal et al. (2016) I report the regression coefficients for each of the regression specifications across the entire time horizon. These can be found in appendix tables A9, A10, and A11.

Appendix C: Numerical Method

Financially ignorant households - decision problem

Here I outline the procedure to calculate the optimal attention paid to future financial variables following Tibshirani 1996 and Gabaix 2014, 2016:

First, let $m_t \in [0,1]$ denote attention weight to payment difference x. Now, two solve the households decision problem I must solve a two-step problem:

1. Choose weight m_t

2. Solve C-S problem with $x_t^s \equiv m_t x_t$

In order to solve this problem we first define out standard value function (capital V):

$$V_t(z_t) = max_{c_t} \left\{ u(c_t, z_t) + \beta \mathbb{E}[V(z_{t+1})] \right\}$$

with state variables: $z_t = \{a_t, y_t, b_t, x_t\}$, a choice variable: c_t, and a transition function: $z_{t+1} = F(c_t, z_t, \epsilon_{t+1})$

Next define lower case 'v':

$$v(c_t, z_t) = u(c_t, z_t) + \beta \mathbb{E}[V(z_{t+1})], \tag{.1}$$

and consider a 2nd order Taylor approximation around $m = 0$.

Now, let the default attention and consumption be $m^d = 0$ and $c^d = \arg\max_c v(x, z, m^d)$, and let $c_m \equiv \frac{\partial c}{\partial m}|_{(m^d, c^d)}$. The sparse max operator, $smax_{c,m}$ is defined by the following procedure (Gabaix, 2014, 2016a,b):

Step 1: *Choose the attention vector m^*:*

$$m^* = \arg \min_{m \in [0.1]} \frac{1}{2} \Lambda (1 - m)^2 + \kappa m \tag{.2}$$

with the cost-of-inattention factor $\Lambda \equiv -\mathbb{E}[c_m V_{cc} c_m]$

Step 2: *Choose choice variables*

$$c^s = \arg \max_c v(c, z, m^*) \tag{.3}$$

and have the resulting utility be $v^s = v(c^s, z)$.

In the numerical exercise, for every simulation draw I follow the following procedure (outlined in Ganong and Noel (2016)) to solve for the optimal attention to the HELOC reset given a κ:

1. Compute $\tilde{c}_t(\tilde{z}_t)$ as the consumption level, so $\tilde{z}$ equals actual income at $t = 0$.

2. Compute $\frac{d\tilde{c}}{dm}$ as the change in consumption from additional attention.

3. For grid values of κ:

   (a) For a seed value of $\tilde{z}$, compute $\tilde{c}_t(\tilde{z})$.

   (b) Compute optimal attention m^* using equation 5.7.

   (c) Calculate perceived income at HELOC reset date T.

   (d) At each date $t \leq T$ the consumer forms a consumption plan c_t^* using perceived $\tilde{z}_t$.

   (e) If the quadratic distance between $\tilde{c}_t^*(m_t^*)$ and $\tilde{c}_t$ is less than 0.0001 continue to the next value in the grid of κ.

   (f) If not, return to step (a) with an alternate value of $\tilde{z}$.

4. Evaluate distance from generated $\{c_t^*(m^*)\}$ to the data. Choose m^* that best fits data.