Building Assets or Increasing Liability? Biased Self-Perceptions of Borrowing Capacity and Financial Decisions of First Time Homebuyers

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Abstract
The recent mortgage crisis calls into question the first time homebuyer's ability to appropriately evaluate and manage debt when making mortgage decisions. In this analysis, we leverage data collected through a field experiment of 573 first time lower income homebuyers in Ohio to investigate the following questions: To what extent do lower-income homebuyers accurately estimate their borrowing capacity, and how does this understanding (or lack thereof) influence decisions regarding their mortgage? Are less knowledgeable homebuyers more or less likely to respond to offers of financial counseling post-purchase? Through multivariate analysis, we evaluate the effect of borrowing capacity (perceived and actual) on administrative mortgage characteristics. We also estimate the probability that borrowers will respond to an offer of financial counseling post-purchase. In both estimations, we include a robust array of demographic and household characteristics, as well as measures of financial confidence, financial literacy, financial support and time preferences. We find that those consumers who underestimate their non-mortgage debt incur significantly higher mortgage debt, relative to income, while homebuyers who overestimate their debt incur lower mortgage debt and are much more likely to take-up financial counseling services. We also find that borrowers who are overconfident in their ability to pay down their debt incur higher mortgage debt and are less likely to take-up financial counseling services. This study offers rare insights into systematic biases in the information that consumers use to make financial decisions relative to the administrative data that firms use. From a policy perceptive, these findings are timely given the ongoing housing crisis and policy debate over extending (or retracting) homeownership to lower income, potentially less informed consumers.

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1. Introduction

For the past several decades, homeownership has been promoted as a tool to build wealth among low and moderate-income (LMI) households. Indeed, equity in a home is the largest source of wealth for LMI households (Green and White 1997; Boehm and Schlottmann 1999). However, the recent mortgage crisis demonstrates that ownership in a home can create a substantial financial hardship, particularly for new homeowners with fewer financial resources to draw upon in times of crisis (Molloy and Shan 2011; Foote, Gerardi, and Willen 2012). Rather than focusing on the asset side of the homeownership balance sheet, this analysis examines consumer decisions regarding the debt to be acquired through purchase. For the LMI homebuyer, the ability to manage the debt burden of a new monthly mortgage payment may be challenging, due to lower financial literacy and numeracy skills (Bucks and Pence 2008; Lax et al. 2004), short-term mental accounting (Cheema and Soman 2006; Heath and Soll 1996; Haveman et al. 2006; Munnell et al. 2007), and less liquidity (Johnson and Li 2011; Van Zandt and Rohe 2011).

In addition to these limitations, we propose that the ability of homebuyers to optimally make decisions regarding mortgage debt requires that they (1) accurately perceive their current debt situation; and (2) use this information to adjust their mortgage decisions. Recent research that suggests individuals may not accurately estimate or self-report financial data about their own balance sheets, including information about debt and credit scores, and that biased estimations may be systematically linked to suboptimal financial decisions (Zinman 2009; Karlan and Zinman 2008; Perry 2008; Levinger et al. 2011). We suggest that biased self-assessments of *borrowing capacity*, defined as the amount of leverage available to consumers and demonstrated ability to repay debt, may be also associated with suboptimal financial decisions including decisions related to mortgage debt. Further, while assistance is often available to help consumers manage debt, there is evidence that those who need help the most based on administrative indicators of financial hardship are often less likely to participate (Meier and Sprenger 2007, 2012; Hung and Yoong 2010; Wang 2010). Little is known about the extent to which perceptions of borrowing capacity, rather than actual borrowing capacity, drive participation in offers of voluntary financial counseling.

We leverage data collected through a field experiment of LMI homebuyers in Ohio to address the following questions: To what extent do LMI homebuyers accurately estimate their overall borrowing capacity, and how does this understanding (or lack thereof) influence decisions regarding their mortgage? Are less knowledgeable homebuyers more or less likely to respond to offers of financial counseling post-purchase? From June to December 2011, 573 homebuyers consented to participate in the study and completed a comprehensive online self-assessment of their financial well-being. A randomly selected sub-sample of these homebuyers was offered financial counseling. We match the self-report data with administrative data drawn from mortgage origination files and credit reports. This unique combination of self-report and administrative data allows us to construct measures of both estimated and actual borrowing capacity based on self-reported debt levels, payment amounts and payment difficulty, compared with credit report data on total debt, monthly payments and payment history.

Through multivariate analysis, we first evaluate the effect of borrowing capacity (estimated and actual) on administrative mortgage characteristics, including full monthly payment and mortgage payment as a proportion of income. Second, we analyze the probability that borrowers will respond to an offer of financial counseling post-purchase, based on their estimated and actual borrowing capacity. In both estimations, we include a robust array of demographic and household characteristics, as well as measures of financial confidence, financial literacy, financial support and time preferences.

In terms of leverage, while most homebuyers in our sample only slightly underestimate their monthly debt, about 11 percent of homebuyers significantly underestimate their monthly debt and 9.5 percent of homebuyers significantly overestimate their monthly debt by about one standard deviation below or above the mean, respectively, measured as a percent of income. Further, 9.5 percent of homebuyers in our sample appear to be overconfident in their ability to repay their debt compared with their actual debt payment history on their credit reports. We find that those consumers who underestimate their non-mortgage debt incur significantly higher mortgage debt, relative to income. We also find that homebuyers who overestimate their debt are more than twice as likely to enroll in and complete financial counseling services. On the other hand, homebuyers who are overconfident in their ability to repay debt are significantly more likely to incur high mortgage leverage (greater than 28% of their income), and are significantly less likely to take up or complete financial counseling.

These findings offer rare insights into systematic biases regarding the information that consumers use to make financial decisions relative to the administrative data that firms use. Our study also sheds light on otherwise unobservable characteristics of consumers (e.g., information bias, inattention, differing time preferences) that may influence the take-up of financial advice or counseling services (Bhattacharya et al. 2012; Hung and Yoong 2010; Meier and Sprenger 2007). Finally, our analysis builds on recent research (Johnson and Li 2010, 2011) incorporating borrowing constraints (debt service ratio) into models of consumer financial decision-making and consumption, in addition to traditional measures of liquidity.

2. Homeownership Decisions and Consumer Vulnerability

The purchase of a first home is likely the largest financial transaction ever made by new homeowners, and the mortgage is the largest debt most have ever incurred (Bricker et al. 2011). Managing mortgage debt can be a significant challenge for new homeowners, and the inability to manage debt can have severe consequences, including foreclosure. For example, in the first quarter of 2012, 11 percent of homeowners were in foreclosure or at least one payment past due, while 60 percent of mortgages for low-income homeowners, originated between 2005 and 2007 at lower credit standards, were three payments or more past due or in foreclosure (Robinson 2012).

While there are numerous causes of mortgage default, debt constrained borrowers with low and moderate incomes are in a particularly precarious position in the face of other triggering events such as job loss, medical expenses, and housing market depreciation. Research on LMI homebuyers documents confounding factors that increase the vulnerability of these consumers, including lower financial literacy and numeracy skills, tighter household budgets, and liquidity and non-mortgage debt borrowing constraints. Home purchase is a complex undertaking, even for individuals with a solid understanding of financial terms. Intimidated by the large sum of money at stake, unfamiliar financial terms (PITI, amortization), and uncertainty about the actual monthly out-of-pocket costs provide a uniquely challenging decision-making context (Bucks and Pence 2008). LMI homebuyers face additional difficulties. These homeowners tend to have lower overall financial literacy, numeracy and financial knowledge, which has been associated with higher borrowing costs and poor debt payment decisions (Soll, Keeney, and Larrick 2012; Lusardi and Tufano 2009). Indeed, LMI homebuyers have been found to make less informed and more costly mortgage decisions (Bucks and Pence 2008)(Lax et al. 2004).

LMI consumers often have tight household budgets that tend to prompt more malleable mental accounting and a focus on shorter term financial decisions (Cheema and Soman 2006; Heath and Soll 1996). These households tend to be less skilled with longer term financial planning tasks, including those related to mortgages (Johnson, Atlas, and Payne 2011). Further, LMI homebuyers may not budget appropriately for non-mortgage expenses associated with homeownership (Van Zandt and Rohe 2006, 2011; Reid 2006; Louie, Belsky, and McArdle 1998). In a study of affordable mortgage borrowers, Van Zandt and Rohe (2011) find that nearly half (48 percent) of new LMI homeowners find themselves confronting major unexpected home repairs, and more than one third reported major unexpected increases in utility costs, property taxes, or homeowner's insurance within the first two years after purchase. Uninformed or non-existent financial plans result in uncertainty about future financial obligations and, in turn, inaccurate estimates of a family's ability to meet monthly housing expenses.

Beyond budgeting shortfalls, a recent research paper reports that many LMI homeowners face liquidity constraints. Van Zandt and Rohe (2011) find an average total savings amount of $3,500 for new LMI homeowners. The ability to meet housing expenses is also influenced by the extent to which a homeowner can access credit. Van Zandt and Rohe find "troubling increases in the use of debt and in the incidence of late debt repayment" among new low-to-moderate income homeowners. Two years after home purchase, more than half of Van Zandt and Rohe's sample of participants in an affordable homeownership pilot program had greater non-housing debt than prior to home purchase, mainly due to medical debt and credit card debt. About one-quarter were late in debt repayment by 30 days or more (Van Zandt and Rohe 2011).

3. Borrowing Constraints and Mortgage Debt

Given the potential challenge of meeting mortgage obligations, particularly for LMI homebuyers, consumers should optimally seek to purchase a home that minimizes their monthly mortgage payment burden (payment to income ratio) while maximizing housing utility (Ambrose and Capone 1998; Dietz and Haurin 2003). In a recent analysis, Johnson and Li (2011) demonstrate that borrowing constraints are an important predictor of consumption decisions along with traditional measures of liquidity constraints. While households may not have enough liquid assets to consume at their desired level (liquidity constrained), they may have access to credit that allows them to borrow up to a desired level. In fact, most consumers make purchase decisions based on the required monthly payment associated with the mortgage rather than the total loan amount or terms, an anchoring effect described in several recent studies (Navarro-Martinez et al. 2011; Stewart 2009). There is a limit on the total debt-to-income ratio permissible by lenders; above certain debt service ratios, consumers are significantly more likely to be turned away for additional credit.

Thus, in addition to considerations of disposable income and liquidity, consumers' decisions regarding optimal mortgage payments are likely made in conjunction with a consideration of other required monthly debt payments. If a household's total monthly debt to income (DTI) ratio is low, i.e., less of consumer's monthly budget is comprised of required debt obligations, the consumer may be willing to incur a greater debt through home purchase and still stay below her optimal threshold. This assessment, however, requires that the consumer estimates her current debt payment burden correctly and that she uses this information to minimize overall borrowing constraints. For homeowners, inaccurate estimates can prove to be costly. If the borrower purchases more home (larger payment) than she would have otherwise purchased had she accurately estimated her debt payment burden, she may be at greater risk for default. Previous research in this area is sparse, due in part to the lack of both self-report and administrative data. Some inroads have been made – for example, Bucks and Pence (2008) have found that borrowers with adjustable-rate mortgages underestimate potential changes in interest rates, and Chan and Stevens (2008) compare pension knowledge and retirement decision-making.

Zinman (2009) reports on debt estimation of consumers and its relationship to administrative data. With regard to accurate estimates, Zinman provides evidence that consumers may severely underestimate their debt. Comparing aggregate self-reported revolving debt balances from the Survey of Consumer Finances (SCF) with aggregate administrative consumer credit data from the Federal Reserve (G.19), Zinman finds that the self-report SCF data underestimate nearly half of total aggregate revolving debt, a trend that is increasing over time. From the aggregate data, it is impossible to identify systematic variation in consumer characteristics that might be associated with underestimation of debt. Such an understanding is critical to not only inform consumer limitations in financial decision making processes, but also to reveal potential biases in research employing self-reported survey data of consumer financial behavior, a limitation noted in several recent studies (Elliehausen and Lawrence 2001; Zinman 2009; Chan and Stevens 2008).

In a survey study, Karlan and Zinman (2008) noted that gender of the respondent and interviewer is correlated with the likelihood of purposely under-reporting high-interest consumer loans. Further, in payday lending, there is evidence that women and LMI consumers may be less likely to report unsecured cash loans that they are administratively known to have (Elliehausen and Lawrence 2001). However, such underreporting has little correlation with creditworthiness, loan repayment behavior, race, or marital status. Zinman (2009) calls for additional research comparing self-report with valid administrative micro-data to further investigate potential factors associated with underreporting, and the impact (if any) of such underreporting on consumer decisions. Our study begins to address this gap within the context of estimated versus actual debt and consumer mortgage decisions.

In addition to initial mortgage decisions regarding how much debt to acquire through purchase, our study considers how estimated versus actual debt influences whether or not consumers accept offers of financial counseling after purchase. The provision of financial education and counseling to homeowners pre and post-purchase is purported to help reduce the vulnerabilities of LMI consumers with regard to managing their new mortgage debt (Wiranowski 2003). However, most counseling services for new homeowners are voluntary, and there is reason to believe that those who need it most may decline to participate. In a study of the take-up of financial advice offered in conjunction with free-tax preparation services, Meier and Sprenger (Meier and Sprenger 2007, 2010) find that those who accept the offer of financial advice have substantially higher discount rates than those who decline advice. Similarly, in a laboratory experiment of portfolio allocation decisions, Hung and Yoong (2010) find that participants who respond voluntarily to the offer of financial advice are more likely to reap positive outcomes from such advice than those who either self-select to decline advice, or those forced to receive advice. Previous research that finds associations between housing counseling interventions and positive outcomes, such as reduced mortgage default, does not account for this potential bias (Hung and Yoong 2010; Quercia and Ding 2009; Rademacher et al. 2010).

4. Data & Methods

4. 1 Study Population

We examine the above propositions using baseline data collected as part of a randomized field experiment of financial planning interventions for first time homebuyers. Study participants are drawn from the Ohio Housing Finance Agency (OHFA)'s First Time Homebuyer Program, which provides affordable fixed-rate mortgage financing funded through tax-exempt Mortgage Revenue Bonds. Nationwide, more than 100,000 LMI first-time homebuyers purchase homes using state Mortgage Revenue Bond programs every year. Ohio Housing Finance Agency's "First-Time Homebuyer Program" is one of the largest in the nation in terms of the number of homebuyers served. By law, Ohio Housing Finance Agency's program serves individuals with household incomes below 115 percent of area median income, or up to 140 percent of median income in federally designated underserved target areas where borrowers are not required to be first-time homebuyers (National Council of State Housing Agencies 2011).

Ohio Housing Finance Agency currently requires all homebuyers receiving down payment assistance to complete its "OHFA's Streamlined Homebuyer Education Program" (OHFA 2008) prior to loan closing. The sampling frame for this study consists of all low and moderate-income prospective homebuyers seeking mortgages through the Ohio Housing Finance Agency's homebuyer program and completing its education component beginning May 20, 2011 through December 31, 2011. During this seven-month time frame, a comprehensive online financial health assessment (designed by the study team, called "MyMoneyPath") was administered to 928 prospective homebuyers completing the education program. Upon completion of the assessment, prospective homebuyers were invited to participate in the study following an IRB approved protocol.[1] Approximately two-thirds of the prospective homebuyers (573, or 62%) consented to participate in the study and were randomly assigned to either the control (33%) or treatment (67%) group. Treatment group participants were offered additional financial planning assistance, including an online financial planning and goal-setting module prior to home purchase and telephone based financial counseling for one year after home purchase.

At the conclusion of the initial data collection period (June 30, 2012), 488 (85%) of the consenting participants purchased a home, of whom 420 have complete data and are included in our study.[2] For the analysis of the take-up of the offer of financial planning assistance after purchase, we limit our sample to those participants who closed on their homes and were assigned to the treatment group to receive an offer of additional financial counseling services (n= 293), of whom 283 had complete data for our analysis.

4.2 Data Sources

Our study affords a unique opportunity to combine comprehensive self-reported indicators of financial health from the online financial health assessment developed for this study (called "MyMoneyPath"), and administrative credit report, origination, and mortgage data collected as part of the loan origination process. The self-assessment collects information on five

[1]Upon completion of the financial assessment, homebuyers were directed to a screen (online) informing them of the opportunity to receive additional free financial planning resources and participate in a study. Full study details were provided, including descriptions of the financial planning resources and confidential use of their data for research, following an IRB approved protocol. After reading the consent information online, participants indicated consent by selecting "I agree" or "I do not agree" to participate in the study and receive additional financial planning resources. Participants who agree to participate receive a $25 Amazon.com gift card via e-mail for their participation.

[2]Due to issues with the data link, initial credit report data was unavailable for a portion of homebuyers. The final sample for this analysis includes only those with complete initial credit report data, reducing the sample to 420 total homebuyers. The model predicting take-up of counseling includes 283 observations with complete data.

areas of financial health: budgeting, borrowing, savings, home, retirement, as well as basic demographic and socio-economic information.[3] The assessment also includes simple measures of confidence regarding finances, time preferences, and financial literacy (Lusardi and Mitchell 2008). Appendix A provides the descriptions of all variables used in our analysis.

In partnership with the Ohio Housing Finance Agency, the self-reported data collected through the financial health assessment is linked to administrative data collected at two points in time for consenting participants: (1) loan application and (2) mortgage origination.[4] The data collected at the time of loan application includes basic demographic information about the borrower, including household income, household composition and occupation. The data collected at mortgage origination includes some demographic information, but also includes characteristics of the mortgage transaction such as mortgage amount, appraised value, and monthly payment (principal, interest, taxes and insurance). The mortgage origination data also includes comprehensive credit report data collected shortly after purchase, upon transfer of the loan to Ohio Housing's Master Servicer.[5] The electronic credit report data includes numerous attributes related to historical and current revolving and installment debt tradelines, including balances and repayment characteristics, as well as public record information (bankruptcies, tax liens and collections).

[3]The indicators of financial health that we included are in line with the U.S. Treasury's recently released "Financial Education Core Competencies" in five key areas: (1) earning, (2) spending, (3) saving, (4) borrowing, and (5) protecting against risk (U.S. Department of Treasury 2010).
[4]The administrative link also includes servicing data with longitudinal (monthly) mortgage payment information, to be used in future analyses.
[5]Credit data will also be provided longitudinally for study participants, at 12 months after origination. This longitudinal data will be used in conjunction with other indicators, to evaluate the effectiveness of the treatment interventions on indicators of financial health.

4.3 Model Variables & Specifications

The purpose of this analysis is to explore the extent to which lower-income homebuyers accurately estimate their overall borrowing capacity, and how this understanding (or lack thereof) influences decisions regarding their mortgage. We consider two mortgage decisions of particular importance to LMI homebuyers: (1) mortgage consumption, or the amount of monthly debt to be acquired through purchase, and (2) take up of financial counseling, or the acceptance of an offer for free financial counseling after purchase.

We hypothesize that these decisions are directly related to the extent to which the LMI consumer accurately estimates his or her borrowing capacity. We further investigate the extent to which other common indicators of financial capability predict mortgage consumption and take-up of financial counseling. Finally, we investigate the extent to which common indicators of financial capability are associated with our measures of biased self-estimations.

Borrowing Capacity

We include two types of indicators for borrowing capacity: non-mortgage borrowing constraints (debt to income ratio), and overconfidence in the ability to pay down debt. On the financial self-assessment completed online prior to home purchase, participants were asked to identify sources of financed debt (using the question – 'check all that apply: Car; Student Loans; Credit Card; Mortgage; Personal Loans; Other Loans'), and were required to estimate the minimum monthly payment and total outstanding balance for each source of debt they identified. To calculate self-estimated borrowing constraints, we summed the monthly payment amounts reported for each participant. We then divided total self- estimated monthly debt by household monthly income (as verified by Ohio Housing Finance Agency), to create the self-estimated debt-to-income (DTI) ratio. The average self-estimated DTI for participants in our sample is 10.8 percent, based on total monthly debt payment of $402, and total reported debt of $21,743 (see Table 1).

[Insert Table 1 Here]

We calculate administrative monthly debt from the credit reports, by summing the total minimum monthly payment for revolving and non-mortgage installment debt. Because of potential inaccuracies with credit report data (Avery et al. 2009), we clean the credit report data with verified data on monthly debt used in the mortgage underwriting decision[6]. To create the administrative DTI ratio, we divide the administrative monthly debt by the verified household monthly income (same denominator as used in the self-estimated DTI). After cleaning the data, the average administrative DTI for participants in our sample is 11.1 percent, based on $413 in monthly minimum debt payments, for total debt of $27,932 (Table 1). We include the administrative ratio for debt-to-income (DTI) to measure actual non-mortgage borrowing constraints.

To identify the extent to which participants under- or overestimate their non-mortgage borrowing constraints, we calculate the difference between self-estimated DTI and administrative DTI. The average difference in our sample is -.4 percent, meaning that the average participant underestimates their monthly DTI by about half a percent. Based on the distribution of the data and the standard deviation (5.7 percent), we code those self-reporting DTI ratios that are 5 percent or less than the administrative DTI as "underestimating", and those self-

[6] On average, the verified monthly debt used in underwriting is higher than the monthly debt included on the credit report. We take the lower of the two administrative estimates for monthly debt. If the credit report monthly debt is higher than the verified monthly debt by $50 or more, we use the verified monthly debt.

reporting DTI ratios that are 5 percent or more the administrative DTI as "overestimating"[7]. In our sample, 11 percent underestimate their debt, while 9.5 percent overestimate their debt (Table 1). We include the two dummy variables for over- and underestimation of DTI in our primary models, with accurate estimations (within 5 percent of the actual DTI) treated as the reference category. Dummy variables are the preferred specification because of the non-linear distribution of the indicator for DTI difference. However, for the mortgage payment models (front end ratio and monthly mortgage payment), we also estimate a specification that includes both continuous measures of DTI-- self-estimated and actual DTI-- to identify which measure is more predictive of mortgage debt incurred.

In addition to indicators of borrowing constraints, we include an indicator of overconfidence in paying down debt. To construct this measure, we combine an indicator for self-reported confidence in "paying off debt" with administrative credit report data on any trade delinquencies in the last 24 months. Specifically, those who self-reported they are "very confident" paying off debt ("4"), but also have a trade that was 60 or more days delinquent within the last 24 months are coded "1" for overconfident, representing 14.3 percent of participants in our sample.

[Insert Table 2 Here]

Mortgage Consumption

In line with industry calculations (Quercia, McCarthy, and Wachter 2003), we measure mortgage consumption as the ratio of the monthly mortgage payment to monthly household income, referred to here as the 'front-end' ratio. The monthly mortgage payment is derived from

[7]We also model alternative cut-off points at 1% and 2.5% to check our specification.

administrative data at the time of origination, and includes principal, interest, taxes, insurance and private mortgage insurance. It is important to note that all mortgages in our sample are 30 year fixed rate, FHA-insured mortgages with the same interest rate at any given point in time as determined by the Ohio Housing Finance Agency. Thus, our study holds constant other consumption decisions typically associated with mortgage transactions (interest rate, loan terms, and fees) that have been found to differ by consumer characteristics (Bucks and Pence 2008; Lax et al. 2004), allowing us to focus specifically on the amount of debt acquired through purchase.

As demonstrated in Table 1, the average mortgage payment for borrowers in our sample is $815, based on an average purchase price of $102,007, with a resulting average front-end ratio of 22.6 percent (range from 7.7 to 51.6 percent). Typically, lenders consider front-end ratios in excess of 28 percent to place consumers at higher risk of mortgage default, including propositions for Qualified Residential Mortgages under the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act.[8] We thus consider 28 percent to be an indicator of high mortgage leverage, indicative of 19 percent of borrowers in our sample. As demonstrated on Table 2, borrowers with high mortgage leverage (greater than 28 percent) have lower non-mortgage debt, on average, although this difference is only statistically significant for self-reported rather than administrative debt (8.3 percent compared with 11.3 percent non-mortgage debt to income). This makes sense, as higher non-mortgage debt reduces the amount of additional borrowing capacity that can be acquired through a mortgage payment. Borrowers with high mortgage leverage also have significantly lower incomes, are less likely to have a college degree, and are more likely to be minority households. Of note, borrowers with high mortgage

[8] Automated underwriting has reduced the use of such ratios as strict cut-off points for mortgage decisions, however, the proposed changes to the lending industry under the Dodd-Frank Wall Street Reform and Consumer Protection Act includes provisions to define a Qualified Residential Mortgage (QRM) based in part on front end ratios below 28 percent (111th United States Congress 2010). In addition to credit, LTV, and down payment requirements, the Dodd-Frank Act provisions currently propose 28% and 36% housing and debt ratios as the cutoff points for a QRM.

leverage are much more likely to be overconfident in their ability to repay their debt, 23.1 percent compared with 12.3 percent of those without high mortgage leverage.

For the multivariate analysis of mortgage debt, we first estimate ordinary least squares (OLS) regressions with front-end ratio and monthly mortgage payment as alternative continuous outcome variables.[9] For each individual *i*, we estimate the equation

$$Y_i = \alpha + \beta\, DTI_i + X_i'\, \delta + \varepsilon \qquad (1)$$

using front-end ratio and monthly mortgage payment amount as alternative outcome variables, *Y*. We include the indicators for borrowing capacity (DTI) as explanatory variables in addition to the vector of financial capability and control variables, *X*. Robust standard errors are calculated to improve model efficiency.

We then estimate the probability that a borrower has high mortgage leverage, defined as a mortgage payment to income ratio of greater than 28 percent. We employ logistic regression due to the binary nature of the dependent variable. For interpretation of the coefficients, we calculate the predicted probability of the change in the outcome variable for a one unit or one standard deviation change in the independent variable. For individual *i*, we use logistic regression to estimate the equation:

$$\Pr\,(Y_i|1)=[1 + \exp\text{-}\,(\alpha - \beta\, DTI_i + X_i'\, \delta)]^{-1} \qquad (2)$$

where Y_i takes the value of 1 if the borrower's mortgage payment exceeds 28 percent of his or her monthly income. We include the indicators for borrowing capacity (DTI) as explanatory variables in addition to the vector of financial capability and control variables, *X)*.

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[9]In alternative specifications, we include total purchase price and purchase price to income as dependent variables, with qualitatively and quantitatively similar results. However, decisions regarding mortgage consumption relative to other debt are more likely made based on monthly mortgage payments, which is the primary model we present in our findings.

Propensity to Take-Up Financial Counseling

About one- third (107 or 37.8 percent) of the 283 study participants who closed on their home and were randomly assigned to the treatment group responded affirmatively to the offer for financial counseling and completed at least one session (see Table 2), and about 19 percent completed all counseling sessions. The breakdown by those who take-up and do not take-up counseling shows that those who respond affirmatively to offer for financial counseling are more likely to inaccurately estimate their borrowing constraints; however, those taking up counseling are about twice as likely to be over-estimators, with 12.1 percent of those taking up counseling overestimating their debt, compared to only 6.3 percent of those not taking up counseling. Further, those who do not take up counseling are more than twice as likely to be overconfident (19.3% compared with 8.4% of those who take up counseling).

We employ a logistic regression model with take-up of financial counseling, and then completion of counseling, as the binary outcome variables. For interpretation of the coefficients, we calculate the predicted probability of the change in the outcome variable for a one unit or one standard deviation change in the independent variable. For individual *i*, we use logistic regression to estimate the equation:

$$\Pr(Y_i|1)=[1 + \exp-(\alpha - \beta\, DTI_i + X_i'\, \delta)]^{-1} \qquad (3)$$

where Y_i takes the value of 1 if the respondents take-up counseling or completes counseling in the alternative model. We include the indicators for borrowing constraints (DTI) as explanatory variables in addition to the vector of financial capability and control variables, *X)*.

Biased Self-Perceptions of Borrowing Capacity

Finally, we estimate models to predict biased perceptions of borrowing capacity, with underestimation of debt, overestimation of debt, and overconfidence as the outcome variables. The purpose of these models is to identify systematic variation in other measures for financial capability and/or our control variables that may be associated with estimation of debt. For our study, these estimations further inform the extent to which biased perceptions of borrowing capacity represent a unique, independent construct.

Because many studies of financial behavior rely on self-reported indicators of debt, such as those based on the Survey of Consumer Finances and the Health and Retirement Study, it is critical to understand the extent to which inaccurate self-estimations are randomly distributed (as is assumed by statistical corrections to self-reported financial data). Knowing the extent to which systematic differences exist is useful and, in turn, may be correlated with other important indicators of financial health or wellbeing (Zinman 2009; Karlan and Zinman 2008).

We employ a logistic regression model with underestimation, overestimation and overconfidence as the binary outcome variables. For interpretation of the coefficients, we calculate the predicted probability of the change in the outcome variable for a one unit or one standard deviation change in the independent variable. For individual i, we use logistic regression to estimate the equation:

$$\Pr (Y_i|1)=[1 + \exp- (\alpha - \beta FC_i + X_i' \delta)]^{-1} \qquad (4)$$

where Y_i takes the value of 1 if the respondents take-up counseling or completes counseling in the alternative model. We include other indicators for financial capability (FC) as explanatory variables in addition to the vector of control variables, X).

Indicators of Financial Capability

In all of our model specifications, we include explanatory variables that capture different components of financial capability, as indicated in Table 2. First, the financial self-assessment includes two simple questions measuring financial literacy taken from Lusardi and Tufano (2009) (see Appendix A for question wording). For our analysis, we assign each participant a score of 0, 1, or 2 based on the number of correct responses; 67% of participants responded correctly to both questions, 27% responded correctly to one question, and 6% responded incorrectly to both financial literacy questions, resulting in an average financial literacy score of 1.61.

Second, the self-assessment includes a three-item indicator of future discounting, based on the participant's preference to receive $40 now, or $50, $60 or $120 a month from now, respectively, modeled after Ashraf, Karlan, and Yin (2005; see also Benzion, Rapoport, and Yagil 1989; Thaler 1981). For our analysis, we include a dummy indicator for the high-discounters who report a preference for $40 now rather than $60 a month from now, corresponding to 8.6 percent of our sample.

Third, the self-assessment includes five questions related to confidence with managing the following financial activities modeled after the financial education core competencies: day-to-day finances, paying off debt, making a mortgage payment, planning for future expenses, and planning for retirement (U.S. Department of the Treasury 2010). Each participant rates his or her confidence on a scale of "1" to "4," where "1" is not at all confident and "4" is very confident. For our analysis, we calculate the summative confidence score for each participant, with a possible range in value from 5 to 20, with a mean score of 17.80. Most of our respondents are very confident in their ability to manage all aspects of their finances.

Finally, the self-assessment asks participants to identify, from a list, sources of financial advice they have used in the past year, including informal sources (friends, relatives and coworkers) and assistance from a professional financial advisor (lawyer, accountant or financial planner). We include a dummy variable coded "1" if participants report seeking help from a professional financial advisor within the past year - 14.5 percent of participants in our sample report seeking such help.

Control Variables

We include a robust array of control variables, including financial indicators and demographic characteristics (Table 2). With regard to financial indicators, we include credit score at the time of loan origination, verified gross household monthly income (divided by 100), the difference between household monthly income and borrower monthly income used in underwriting (to capture additional or reduced household income not included in the underwriting decision), and total amount of money in checking and savings accounts (logged). In terms of demographic indicators, we include gender (female), age of principal borrower, highest level of education completed (coded "1" if participant completed 4 years or more of college), minority status (coded "1" if participant is black or Hispanic), household size, and time between the initial self-assessment date and credit report pull date (measured in days, logged).

5. Findings

5.1 Borrowing Capacity and Mortgage Debt

To explore the relationship between self-perceived and actual borrowing capacity and mortgage debt, we first estimate the OLS model in Equation 1 with the front-end ratio as the dependent variable, first with the under- and overestimation DTI in categories (Table 3, column 1) and then with the continuous measures for self-reported and actual DTI (column 2). We then estimate the OLS mode1 in Equation 1 with the full monthly mortgage payment as the dependent variable, again with under-and overestimation of DTI, followed by continuous measures of DTI (Table 3, columns 3 & 4). We find evidence that underestimation of debt is significantly associated with increased mortgage consumption. Specifically, those who underestimate their non-mortgage debt (DTI) by 5% or more have front-end ratios that are 2.2 percent higher, on average, holding constant other model variables. Similarly, those who underestimate their DTI have actual monthly mortgage payments that are $80 higher, on average, than those who accurately estimate their borrowing constraints. Conversely, those who overestimate their borrowing constraints have front-end ratios that are 2.1 percent lower, on average, corresponding to mortgage payment that are on average $73 lower.

As would be expected, an overall increase in actual borrowing constraints, measured by the debt-to-income ratio, is associated with significantly lower front-end ratios and the total mortgage payments. This suggests that borrowing constraints in general influence consumer decisions regarding mortgages as would be expected (Johnson and Li 2011). However, as our data show, self-reported borrowing constraints are more significant predictors of mortgage debt than actual borrowing constraints, suggesting that perceptions of debt are guiding decisions more than verified debt (as reported to the lender).

Aside from measures of borrowing constraints, there is also a significant relationship between overconfidence and mortgage debt, where those who are overconfident in their ability to pay off debt have front end ratios that are 1.6 percent higher, on average, and mortgage payments that are $54 higher, on average, than other consumers. This may suggest that those who are overconfident in their ability to meet their non-mortgage debt obligations are willing to take on more mortgage debt. Other indicators of financial capability, including indicators for financial literacy, financial confidence, future discounting, and credit, are not significantly associated with mortgage debt.

Not surprisingly, we also find that income is significantly associated with front-end ratio and monthly housing payment, but in opposite directions. Because monthly income is a component of the front-end ratio (denominator), an increase in monthly income is associated with a decrease in the front-end ratio. On the other hand, those with higher incomes have more money available for housing. Thus, when the dependent variable is measured as the monthly mortgage payment, higher incomes are associated with higher mortgage payments. Further, an increase in the income reported to the bank as a proportion of income verified by the program is associated with higher mortgage payments, an additional measure of resources available for consumption. Controlling for other model covariates, minority borrowers and borrowers with a college degree tend to have higher front-end ratios and mortgage payments.

[Insert Table 3 Here]

In addition to considering mortgage debt as a continuous variable, we consider high mortgage debt burden as mortgage payments that comprise more than 28 percent of monthly household income. Table 4 provides the results of the logistic regression estimations for high mortgage debt burden. Overall, an increase in non-mortgage debt is associated with a decreased probability of incurring high mortgage debt, as would be expected (those with high non-mortgage debt have less borrowing capacity for additional mortgage consumption). Measures for under and overestimation of debt are not significantly associated with high mortgage debt burden. However, borrowers who are overconfident in their ability to pay down debt are more than twice as likely to have high mortgage debt burden (an increased probability of 7 percent). An increase in household income is associated with a reduced probability of high mortgage debt burden. Minority borrowers are significantly more likely to have high mortgage debt burden. Other model covariates are not statistically significant.

[Insert Table 4 Here]

5.2 Predicting Take-Up of Financial Counseling

Next, we estimate the logistic regression model in Equation 2 to predict take-up and completion of the offer for financial counseling after home purchase (Table 4). Our results, after controlling for other model covariates, largely confirm the descriptive differences reported in Table 2. Those who overestimate their DTI (by 5 percent or more) are 21.7 percent more likely to take up the offer of financial counseling and 12.9 percent more likely to complete counseling than those who accurately estimate their debt. This suggests that those who perceive themselves as having greater borrowing constraints are more likely to take up an offer for counseling. This is in comparison to a negative coefficient associated with an increase in actual borrowing constraints, suggesting that it is the perception of constraints rather than actual constraints that drive borrowers to seek help.

Further, we find a significant relationship between overconfidence and the probability of taking up and completing counseling. Those who are overconfident in their ability to pay off their debt are significantly less likely (24.1percent) to take-up the offer of financial counseling and less likely (6.6 percent) to complete counseling.

We also find that females are more likely to take up counseling (15.9 percent). Further, those with a college degree are significantly more likely to follow through and complete counseling (10.2 percent). Finally, there are significant differences by financial coach offering the counseling, where two of the four coaches have a much higher take-up rate of assigned clients than others. While all coaches followed the same protocol for client outreach and enrollment (and all were employed by the same organization), there may be differences in tone and persistence between coaches that can explain some of this variation. Other model covariates, including credit score, financial literacy, income and demographics are not significantly predictive of the take-up of financial counseling.

[Insert Table 5 Here]

5.3 Predicting Biased Self-Perceptions

We estimate the logistic regressions in Equation 3 to predict underestimation of debt, overestimation of debt, and overconfidence (Table 5). Interestingly, none of the financial capability covariates are associated with biased self-perceptions. Measures of financial literacy, overall financial confidence, future discounting and professional advice are not significantly associated with biased estimation, suggesting that estimation of borrowing capacity may be a relatively unique construct. Those with higher overall DTI are significantly more likely to underestimate their DTI, which makes sense, as they have a larger margin for error.

An increase in credit score is associated with a reduced probability of overconfidence and debt underestimation. Income is not associated with debt estimation, however, an increase in household income relative to borrower income is associated with a slight decrease in the probability of underestimating debt, perhaps suggesting additional income that might reduce the income used to calculate DTI and thus increase the probability of underestimation. A few of the demographic characteristics are associated with estimation, where older borrowers are less likely to be overconfident, those with a college degree are more likely to overestimate their DTI, and minority consumers are much more likely to underestimate their debt.

[Insert Table 5 Here]

6. Conclusions

Using a unique sample with self- report and administrative data, our analysis provides evidence that self-perceptions of borrowing capacity are an important, unique component of LMI consumer mortgage decisions. First, we document a relationship between inaccurate estimations of debt and consumer behavior, in this case, mortgage consumption. One of the concerns about self-reported financial data is that there may be systematic variation in the financial behaviors of those who inaccurately estimate their financial situation (Zinman 2009). In terms of underestimating debt, we do find preliminary evidence that inaccuracies may be associated with mortgage consumption behaviors. While an increase in actual borrowing constraints results in less mortgage consumption than would be expected (Johnson and Li 2011), those who underestimate their non-mortgage borrowing constraints systematically consume more mortgage debt relative to those who accurately estimate their borrowing constraints.

We also document a relationship between overconfidence in one's ability to pay down debt and higher mortgage debt (including an increased probability of mortgage debt that is greater than 28 percent of income). Aside from implications for research, our findings that biased self-estimations of borrowing capacity are associated with higher mortgage consumption has significant policy implications. It confirms the notion that not only financial information and financial literacy, but also financial conscientiousness, a term referring to a "consumer regularly attending to financial matters in an organized, orderly, and precise manner" (Bone 2008, 176), is essential in making financial decisions well. To the extent that the borrower consumes more housing than he or she would otherwise consume in light of accurate information, the uninformed LMI homebuyer may be at an increased risk of mortgage default. This suggests that a potentially important role for pre-purchase homebuyer education and counseling is to increase consumer awareness of their own financial situation, in addition to educating about homeownership and financial management. Personalized advice, rather than generic educational literature, may be most appropriate to meet this need. As the housing counseling industry shifts to online and technology based financial education platforms, it becomes possible and relevant to identify innovative and cost-effective strategies to tailor information to individual financial situations (e.g., Servon and Kaestner 2008).

Second, our study sheds light on the factors that predict take-up of financial counseling. We find that borrowers who overestimate their monthly debt are significantly more likely to take up financial counseling. Thus perceptions of borrowing constraints, rather than actual constraints, likely drive participation in voluntary financial counseling and advice. Building on Meier and Sprenger (2012), we also find that those who are overconfident in their own ability to pay down their debt, relative to their actual debt repayment behavior, are less likely to take-up offers for counseling. Our findings contribute to the growing literature on the relationship between need and take up of counseling (Hung and Yoong 2010; Meier and Sprenger 2007; 2012). On one hand, the finding that borrowers who incorrectly estimate their debt are more likely to take up counseling relative to borrowers who estimate accurately suggests that those who take up counseling are in more need than those who do not. On the other hand, the finding that overconfidence in debt repayment predicts less take-up of counseling suggests that those in most need do not take up counseling.

Finally, it appears that biased self-estimations of borrowing capacity are uncorrelated with most other common measures of financial capability, an unexpected finding considering results of a study on overestimation of credit scores (Perry 2008). This may suggest that accurate estimation of borrowing constraints is a unique construct that can contribute to understanding of financial behaviors. This also implies that it may be difficult to control for any bias introduced by inaccurate estimations from self-reported data. Other self-reported indicators of financial capability, such as financial literacy, financial advice and temporal discounting, do not appear to be suitable proxies for inaccurate estimations of borrowing capacity.

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Table 1: Mortgage & Debt Characteristics

	Mean	SD	Min	Max
Mortgage Characteristics				
Front End Ratio	22.6%	6.9%	7.7%	51.6%
Mortgage Payment	$815	249	266	1,713
Purchase Price	$102,007	35,910	22,000	247,000
Interest Rate	4.6%	0.3%	3.8%	5.3%
LTV Ratio	93.6%	6.6%	53.8%	106.5%
Self-Estimated Debt				
Monthly Debt Estimate	$402	297	0	2,000
Monthly Installment Debt	$111	119	0	1,000
Monthly Revolving Debt	$318	269	0	2,000
Monthly DTI	10.8%	7.8%	0.0%	51.6%
Total Debt	$21,743	24,000	0	183,200
Administrative Debt (Credit Report)				
Monthly Debt Estimate	$469	327	0	1,857
Monthly Installment Debt	$351	281	0	1,472
Monthly Revolving Debt	$118	141	0	910
Monthly DTI	12.8%	9.2%	0.0%	78.6%
Total Debt	$27,932	26,299	0	123,955
Administrative Debt (Cleaned with Underwriting)[1]				
Monthly Debt Estimate	$413	304	0	1,693
Monthly DTI	11.1%	8.1%	0.0%	78.6%
Debt Estimation Accuracy				
DTI Difference	-0.4%	5.7%	-29.3%	48.0%
DTI Underestimate <-5%	11.0%	31.3%	0	1
DTI Overestimate >5%	9.5%	29.4%	0	1

N=420

[1]Administrative debt from the credit report is replaced with monthly debt verified during the underwriting process for about 20 percent of borrowers, where the credit report debt is higher than the verified monthly debt by $50 or more.

Table 2: Descriptive Statistics

	Full Sample				High Leverage (Front End > 28%)			Take-Up Counseling		
	N=420				*n=78* *18.6%*	*N=342* *81.4%*		*n=107* *37.8%*	*N=176* *62.2%*	
	Mean	SD	Min	Max	Yes	No		Yes	No	
Borrowing Constraints Indicators										
DTI Administrative	11.1%	8.1%	0.0%	78.6%	11.9%	13.0%		11.8%	13.3%	
DTI Self-Report	10.8%	7.8%	0.0%	51.6%	8.3%	11.3%	**	9.4%	10.8%	
DTI Difference	-0.4%	5.7%	-29.3%	48.0%	-0.8%	-0.3%		0.3%	-0.9%	*
DTI Underestimate <-5%	11.0%	31.3%	0	1	12.8%	10.5%		10.3%	11.4%	
DTI Overestimate >5%	9.5%	29.4%	0	1	6.4%	10.2%		12.1%	6.3%	^
Financial Capability Indicators										
Financial Literacy	1.61	0.59	0	2	1.67	1.60		1.56	1.60	
Professional Advice	14.5%	35.3%	0	1	17.9%	13.7%		13.1%	14.2%	
Future Discounting	8.6%	0.28	0	1	5.1%	9.4%		5.6%	10.2%	
Financial Confidence	17.89	1.91	10	20	18.04	17.85		18.01	17.80	
Overconfidence	14.3%	0.35	0	1	23.1%	12.3%	**	8.4%	19.3%	**
Control Variables										
Credit Score	668.29	50.36	495	795	661.03	669.94		669.06	661.99	
Monthly Income (hundreds)	37.70	12.08	8.43	70.01	29.47	39.58	**	36.65	37.88	
Household Income Difference	4.31	10.15	-82.02	39.97	-0.02	5.30	**	4.46	4.95	
Amount Saved (logged)	5.54	3.63	0.00	10.11	5.30	5.60		5.22	5.41	
Female	46.0%	49.9%	0	1	43.6%	46.5%		57.9%	38.6%	**
Borrower Age	32.77	10.17	20	89	33.33	32.64		32.99	32.49	
Education College	35.2%	47.8%	0	1	29.5%	36.5%	^	34.6%	33.5%	
Minority	14.3%	35.0%	0	1	21.8%	12.6%	*	19.6%	11.9%	^
Household Size	2.44	1.30	1	7	2.29	2.48		2.48	2.47	
Days to credit data (logged)	4.43	0.33	2.08	5.73	4.44	4.43		4.43	4.42	

^p<0.10, * p<0.05, ** p<0.01 (Based on t-test for means and Chi2 test for proportions)

Table 3: Regression Predicting Mortgage Debt (OLS)

	(1) Front-End Ratio			(2) Front-End Ratio			(3) Mortgage Payment			(4) Mortgage Payment		
	β		Robust SE	β		Robust SE	β		Robust SE	β		Robust SE
Administrative DTI	-0.239	**	0.057	-0.118		0.079	-779.500	**	121.897	-319.05	^	179.83
Self-Reported DTI				-0.112	*	0.057				-440.18	*	181.94
DTI Underestimate <-5%	0.022	*	0.009				80.205	*	32.009			
DTI Overestimate >5%	-0.021	*	0.010				-72.835	*	32.589			
Financial Literacy	0.007		0.004	0.007		0.004	23.839		16.834	22.70		16.71
Professional Advice	0.003		0.009	0.003		0.009	15.430		28.311	11.94		28.70
Future Discounting	0.000		0.009	0.000		0.009	-18.866		29.826	-17.35		30.06
Financial Confidence	0.001		0.001	0.001		0.001	0.555		5.157	1.23		5.11
Overconfidence	0.016	^	0.009	0.016	^	0.009	54.411	^	29.382	54.23	^	29.43
Credit Score	0.000		0.000	0.000		0.000	-0.043		0.202	-0.11		0.20
Monthly Income (hundreds)	-0.003	**	0.000	-0.003	**	0.000	13.076	**	1.028	13.13	**	1.04
Household Income Diff.	-0.001		0.001	-0.001		0.001	-8.747	**	1.657	-8.76	**	1.72
Amount Saved (logged)	0.000		0.001	0.000		0.001	-0.347		2.728	-0.31		2.76
Female	0.001		0.006	0.002		0.006	-2.745		20.250	-1.50		20.45
Borrower Age	0.000		0.000	0.000		0.000	-0.773		0.982	-0.59		0.99
Education College	0.014	*	0.006	0.014	*	0.006	56.285	*	23.269	56.45	*	23.59
Minority	0.023	**	0.008	0.023	**	0.008	91.854	**	30.411	90.94	**	30.73
Household Size	0.002		0.002	0.002		0.002	7.618		8.584	8.13		8.66
Days to credit data	-0.002		0.009	-0.001		0.009	-23.298		27.288	-17.99		27.50
Constant	0.354	**	0.063	0.353	**	0.064	496.658	*	212.963	494.62	*	213.31
R-Squared	0.372	**		0.362	**		0.430	**		0.421	**	

N=420; OLS with robust standard errors

^p<0.10, * p<0.05, ** p<0.01

Table 4: Predicting High Mortgage Debt (Logit)

	(1) Front End Ratio > 28%				(2) Front End Ratio > 28%			
	β	Robust SE	Δ Pr[1]		β	Robust SE	Δ Pr[1]	
Administrative DTI	-1.899	3.132	-1.05%		-7.275	2.290	-4.19%	**
Self-Reported DTI	-5.578	3.156	-3.18%	^				
DTI Underestimate <-5%					0.402	0.518	3.59%	
DTI Overestimate >5%					-0.958	0.683	-4.90%	
Financial Literacy	0.260	0.248	1.13%		0.252	0.250	1.13%	
Professional Advice	0.517	0.421	4.70%		0.536	0.409	5.05%	
Future Discounting	-0.287	0.587	-1.86%		-0.302	0.592	-2.01%	
Financial Confidence	0.022	0.079	0.31%		0.029	0.078	0.42%	
Overconfidence	0.778	0.392	7.88%	*	0.802	0.395	8.42%	*
Credit Score	-0.002	0.003	-0.55%		-0.001	0.003	-0.47%	
Monthly Income (hundreds)	-0.079	0.020	-7.16%	**	-0.082	0.021	-7.60%	**
Household Income Difference	-0.038	0.043	-2.82%		-0.032	0.040	-2.48%	
Amount Saved (logged)	0.026	0.043	0.68%		0.030	0.043	0.81%	
Female	-0.409	0.307	-3.55%		-0.388	0.305	-3.45%	
Borrower Age	-0.004	0.015	-0.30%		-0.003	0.015	-0.21%	
Education College	-0.088	0.363	-0.62%		-0.054	0.366	-0.40%	
Minority	1.070	0.387	12.17%	**	1.067	0.397	12.44%	**
Household Size	-0.065	0.118	-0.61%		-0.073	0.119	-0.71%	
Days to credit data	-0.194	0.403	-0.47%		-0.222	0.403	-0.55%	
Constant	3.125	3.339			2.979	3.379		
Psuedo R-Squared	0.2043	**			0.2054	**		
Base Pr (Y)			7.95%				8.22%	

N=283; Logistic regression model with robust standard errors

^p<0.10, * p<0.05, ** p<0.01

[1]Change in the predicted probability for a one unit change or a one standard deviation change, holding all other variables at their mean (or modal) values

Table 5: Predicting Take-Up of Financial Counseling (Logit)

	(1) Take-Up Counseling				(2) Completed Counseling			
	β	Robust SE	Δ Pr[1]		β	Robust SE	Δ Pr[1]	
DTI Administrative	-5.178	2.216	-11.01%	*	-1.938	2.583	1.43%	
DTI Underestimate <-5%	0.445	0.516	11.06%		0.071	0.634	0.63%	
DTI Overestimate >5%	0.900	0.552	21.72%	^	1.011	0.478	12.88%	*
Financial Literacy	-0.153	0.247	-2.29%		0.161	0.296	0.83%	
Professional Advice	-0.255	0.403	-6.22%		0.168	0.474	0.50%	
Future Discounting	-0.533	0.542	-12.65%		-0.714	0.820	-4.61%	
Financial Confidence	0.118	0.083	5.65%		0.110	0.104	1.83%	
Overconfidence	-1.117	0.465	-24.11%	*	-1.256	0.607	-6.59%	*
Credit Score	0.003	0.003	3.55%		-0.001	0.004	0.44%	
Monthly Income (hundreds)	0.009	0.014	2.72%		-0.016	0.018	1.71%	
Household Income Difference	-0.028	0.019	-6.79%		-0.014	0.022	1.14%	
Amount Saved (logged)	-0.065	0.043	-5.99%		0.023	0.050	0.72%	
Female	0.685	0.283	15.92%	*	-0.237	0.358	-2.24%	
Borrower Age	-0.007	0.015	-1.70%		-0.010	0.020	0.84%	
Education College	-0.001	0.331	-0.03%		0.849	0.417	10.20%	*
Minority	0.401	0.407	9.99%		0.682	0.444	7.68%	
Household Size	0.068	0.115	2.18%		0.233	0.131	2.61%	*
Days to credit data	-0.310	0.421	-2.51%		-0.915	0.499	-2.57%	^
Coach (a)	1.223	0.416	29.59%	**	1.815	0.531	22.11%	**
Coach (b)	1.467	0.406	34.58%	**	1.473	0.528	18.07%	**
Coach (c)	0.052	0.401	1.30%		-0.402	0.667	-3.19%	
Constant	-3.201	3.497			0.302	3.934		
Psuedo R-Squared	0.1439	**			0.1775	**		
Base Pr (Y)			45.74%				9.49%	

N=283; Logistic regression model with robust standard errors

^p<0.10, * p<0.05, ** p<0.01

[1]Change in the predicted probability for a one unit change or a one standard deviation change, holding all other variables at their mean (or modal) values

Table 6: Logistic Regressions Predicting Biased Self Perceptions

	(1) Overconfidence			(2) Underestimate DTI			(3) Overestimate DTI		
	β		Δ Pr[1]	β		Δ Pr[1]	β		Δ Pr[1]
DTI Administrative	0.696		0.41%	17.256	**	7.32%	-4.742	*	-1.52%
DTI Underestimate <-5%	0.518		4.62%						
DTI Overestimate >5%	0.391		3.31%						
Financial Literacy	-0.176		-0.75%	-0.108		-0.32%	-0.303		-0.70%
Professional Advice	0.225		1.77%	-0.244		-1.08%	0.225		0.98%
Future Discounting	0.311		2.54%	-0.770		-1.06%	-0.672		-1.95%
Financial Confidence				0.054		0.51%	0.027		0.20%
Overconfidence				0.431		2.58%	0.350		1.61%
Credit Score	-0.023	**	-8.51%	-0.008	*	-2.08%	0.003		0.55%
Monthly Income (hundreds)	0.008		0.69%	0.010		0.61%	-0.013		-0.62%
Household Income Difference	-0.040		-2.89%	-0.039	*	-1.97%	-0.005		-0.20%
Amount Saved (logged)	-0.022		-0.58%	-0.006		-0.10%	0.022		0.31%
Female	-0.027		-0.19%	0.105		0.49%	-0.610	^	-3.18%
Borrower Age	-0.040	**	-2.90%	0.017		0.84%	0.000		-0.01%
Education College	0.182		1.41%	-0.059		-0.28%	0.821	*	4.73%
Minority	0.128		0.97%	0.822	*	5.89%	0.488		2.40%
Household Size	-0.077		-0.72%	0.103		0.66%	-0.041		-0.21%
Days to credit data	-0.335		-0.79%	0.699		1.14%	-0.492		-0.64%
Constant	16.005			-4.234			-1.195		
Base Pr (Y)									
Psuedo R-Squared	0.159		7.77%	0.278	**	5.19%	0.064		4.08%

N=420; Logistic Regression models with robust standard errors

^p<0.10, * p<0.05, ** p<0.01

[1]Change in the predicted probability for a one unit change or a one standard deviation change, holding all other variables at their mean (or modal) values

Appendix A: Variable Descriptions

Variable Name	Description
Administrative DTI	Administrative Debt to Income (DTI) ratio, verified monthly debt/ household monthly income
Self-Reported DTI	Self- Report Debt to Income (DTI) ratio, self-reported monthly debt/ household monthly income
DTI Underestimate <-5%	Difference between Self-Reported DTI and Administrative DTI is < -5%
DTI Overestimate >5%	Difference between Self-Reported DTI and Administrative DTI is > 5%
Financial Literacy	Summative score ranging from 0-2 based on correct responses to interest inflation literacy:
Interest Literacy	Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? More than $102; Exactly $102; Less than $102;
Inflation Literacy	Imagine that the interest rate on your savings account was 1% per year & inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? More than today; Exactly the same; Less than today
Professional Advice	Coded 0-1, based on seeking financial advice or information from a "Professional Financial Advisor (such as lawyer, accountant, or financial planner)" within the last 12 months
Future Discounting	Coded 0-1, based on response to the following question: "Would you rather get $40 now or $60 a month from now", where those preferring $40 now are coded "1".
Financial Confidence	Summative index ranging from 5 to 20 based on responses to 5 items on a scale of 1 to 4, where 1= not at all confident and 4= very confident. The 5 items include: paying for day to day expenses, paying off debt, making mortgage payment, planning for future expenses, and planning for retirement).
Overconfidence	Coded 0-1, where code=1 if the borrower was ever delinquent on a trade on their credit report within the last 24 months, and borrower self-rated their confidence with "paying off debt" as "very confident".
Credit Score	Median credit score from credit report file
Monthly Income (hundreds)	Monthly household income (divided by 100), as verified by the state Housing Finance Agency. Includes verified income from all household members (even if not listed as a co-borrower)
Household Income Difference	The difference between Household Income and Underwriting Income (divided by 100), where a larger number means additional household income not included in underwriting the mortgage
Amount Saved (logged)	Amount in savings and checking accounts, logged
Female	Coded 0-1, where code is 1 if the respondent is female
Borrower Age	Age, in years, of the primary borrower (respondent)
Education College	Coded 0-1, where code is 1 if highest level of education completed is four year college or greater
Minority	Coded 0-1, where code is 1 if Black, Hispanic or Other
Household Size	Number of people in the household
Days to credit data	Number of days between completion of self-assessment and credit report pull, logged