STEPHANIE MOULTON, CÄZILIA LOIBL, ANYA SAMAK, AND J. MICHAEL COLLINS

Borrowing Capacity and Financial Decisions of Low-to-Moderate Income First-Time Homebuyers

This study documents the extent to which first-time homebuyers seeking a mortgage accurately estimate their borrowing capacity and how this is associated with their decisions regarding mortgage debt and the take-up of a free offer of financial coaching. We find that consumers who underestimate their nonmortgage debt (31.5% of the sample) also take out larger mortgages relative to income. Consumers who underestimate or overestimate their total debt as well as their monthly debt payments are more likely to accept the offer of financial coaching. Moreover, overconfidence in financial matters reduces the take-up of financial coaching. These biases in perceived financial status appear to be systematically related to behavior among a group of relatively inexperienced consumers. These findings suggest that efforts to extend homeownership may need to include debiasing mechanisms to help less informed consumers accurately assess their current debt levels and ability to make ongoing mortgage payments.

Equity in a home has traditionally been the largest source of wealth for low- and moderate-income (LMI) households (Boehm and Schlottmann 1999; Bricker et al. 2012; Green and White 1997). However, homeownership and associated mortgage debt can create a substantial financial burden for new homeowners, who tend to have fewer financial resources to draw upon in times of crisis (Foote, Gerardi, and Willen 2012; Molloy and Shan 2011), lower financial literacy and numeracy skills (Lax et al. 2004), and less liquidity (Johnson and Li 2011; Van Zandt and Rohe 2011).

Making an informed decision about how much mortgage debt is manageable requires a consumer to accurately perceive his or her financial

Stephanie Moulton (moulton.23@osu.edu) and Cäzilia Loibl (loibl.3@osu.edu) are both Associate Professors at The Ohio State University. Anya Samak (asamak@wisc.edu) is an Assistant Professor, and J. Michael Collins (jmcollins@wisc.edu) is an Associate Professor, both at the University of Wisconsin-Madison. The research reported herein was performed pursuant to grants from the US Social Security Administration (SSA) funded as part of the Financial Literacy Research Consortium and from The Ohio State University's Office of University Outreach and Engagement. The opinions and conclusions expressed are solely those of the authors and do not represent the opinions or policy of SSA or any agency of the federal government.

The Journal of Consumer Affairs, Fall 2013: 375–403
DOI: 10.1111/joca.12021

situation. However, recent research suggests that individuals may not accurately estimate their own financial status, including information about debt and creditworthiness, and that biased estimations may be systematically linked to suboptimal financial decisions (Bucks and Pence 2008; Karlan and Zinman 2008; Perry 2008; Zinman 2009). We extend this literature with a focus on self-assessments of *borrowing capacity*, defined here as the total amount of consumer debt held by a borrower and associated monthly payments, relative to monthly income. We propose that perceptions of borrowing capacity may also be biased, and that this bias may be associated with suboptimal financial decisions. To the extent that misperceptions of nonmortgage debt result in borrowing more mortgage debt than would be borrowed with accurate information, debiasing perceptions may be an important component of preparing LMI borrowers for home purchase.

We use data collected as part of a field experiment of LMI homebuyers to address the following questions: (1) To what extent do LMI homebuyers accurately estimate their overall borrowing capacity? (2) How does the accuracy of estimates influence decisions regarding mortgage debt and the take-up of financial coaching? Using self-assessment surveys matched with data from mortgage applications and credit reports, this study is able to compare estimated and actual borrowing capacity, and then observe differences in subsequent mortgage borrowing and participation in financial coaching. We find that consumers who underestimate their amount of nonmortgage debt (31.5% of the sample) also take out larger mortgages and have higher mortgage payments relative to income. Consumers who over- or underestimate their total debt and monthly debt payments are more likely to accept the offer of financial coaching. However, overconfidence in financial matters reduces the take-up of financial coaching. These findings offer insights into systematic biases regarding the information that consumers use to make financial decisions relative to the administrative data that firms use.

BORROWING CAPACITY AND MORTGAGE DEBT

The purchase of a home is among the largest financial transactions consumers ever undertake, and the mortgage is the largest debt most consumers ever incur (Bricker et al. 2012). The inability to manage mortgage debt can have severe consequences, including default and foreclosure. Home purchase is a complex undertaking, even for individuals with a solid understanding of financial terms (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 higher payment defaults (Lusardi and Tufano 2009; Soll, Keeney, and Larrick 2013). Indeed, LMI homebuyers tend to incur higher cost loans, have less understanding of loan terms, and have lower probability of refinancing a high-cost loan (Bucks and Pence 2008; Lax et al. 2004).

Prior studies suggest that LMI consumers often focus on shorter-term financial horizons (Cheema and Soman 2006; Heath and Soll 1996) and are 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 nonmortgage expenses associated with homeownership (Louie, Belsky, and McArdle 1998; Reid 2006; Van Zandt and Rohe 2006, 2011). In a study of affordable mortgage borrowers, Van Zandt and Rohe (2011) find that nearly half of new LMI homeowners experienced 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. Similarly, in a study of a small group of low-income homeowners in Florida, Acquaye (2011) finds that only 15% of respondents saved for home maintenance and repairs while 83% of homes aged 10 years or older had maintenance or repair problems, such as broken sideboards or malfunctioning plumbing and air conditioning systems. In line with this research, we propose that uninformed or nonexistent financial plans result in uncertainty about future financial obligations and inaccurate estimates of a family's ability to meet monthly housing expenses in the future.

Given the potential challenges of meeting mortgage obligations, particularly for LMI homebuyers, decisions about the amount of debt to acquire through a mortgage represent an important consumption decision (Ambrose and Capone 1998; Dietz and Haurin 2003). Like other consumption decisions, the amount of mortgage acquired depends not only on access to available assets (liquidity), but also on access to and preferences regarding borrowing (Johnson and Li 2011). In terms of access to borrowing, there is often an underwriting limit on the total debt-to-income (DTI) ratio permissible by lenders. The amount of mortgage for which a consumer qualifies is limited by the consumer's existing debt. Traditionally, the mortgage payment plus all other financed debt payments were limited to 41% of the borrower's income. However, with automated underwriting that incorporates other factors (credit score, income, and savings), this amount can be much higher, as high as 60% of income (Collins, Belsky, and Case 2005). The amount of mortgage for which a borrower qualifies based on underwriting may be well above an amount that the borrower thinks he or she can reasonably afford in light of other monthly expenses.

Thus, while administrative indicators may influence the maximum amount of mortgage debt available (based on qualifying ratios), consumers are also influenced by perceptions of their own borrowing capacity. If a consumer perceives her total monthly nonmortgage debt to be low, the consumer may be willing to take on a larger mortgage through home purchase. In fact, most consumers make purchase decisions based on the required monthly payment associated with the mortgage rather than the total loan amount or loan terms, an anchoring effect described in several recent studies (Navarro-Martinez et al. 2011; Stewart 2009). Thus, consumers' decisions regarding their mortgage are likely made in conjunction with a consideration of other consumer debt and required monthly payments. This assessment, however, assumes that the consumer estimates her current debt correctly and that she uses this information to minimize future indebtedness. For homeowners, inaccurate estimates can prove to be costly. If the borrower purchases more home (larger mortgage) than she would have otherwise purchased had she accurately estimated her debt, she may be at a greater risk for default.

Previous research in this area suggests that consumers tend to 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 (2009) finds that the self-reported 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, or the impact of such underestimation on subsequent behavior. Such an understanding is critical to not only understand consumer limitations in the financial decision-making processes, but also to reveal potential biases in existing research that employs self-reported survey data of consumer financial behavior, a limitation noted in several recent studies (Chan and Stevens 2008; Elliehausen and Lawrence 2001; Zinman 2009).

In a survey study, Karlan and Zinman (2008) noted that the gender of the respondent and interviewer is correlated with the likelihood of purposely underreporting high-interest consumer loans. Further, 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, the researchers find that such underreporting has little correlation with creditworthiness, loan repayment behavior, race, or marital status. Zinman (2009) calls for additional research comparing self-reported with valid agency-reported micro-data to further investigate potential factors associated with underreporting, and the impact (if any) of such underreporting on consumer decisions.

Studies of consumer creditworthiness more broadly find that biased consumer self-assessments may be systematically associated with poor financial decisions, at times with costly consequences (Courchane, Gailey, and Zorn 2008; Levinger, Benton, and Meier 2011; Perry 2008). For example, Courchane et al. (2008) investigate the relationship between self-estimation of credit quality and actual credit score, using consumer survey data and administrative mortgage data collected by Freddie Mac. The authors find some evidence that consumers who inaccurately assess their credit quality are more likely to have been denied credit or to have experienced a negative financial event, such as an eviction or repossession procedure. In a similar study of survey data, Perry (2008) finds that consumers tend to overestimate their credit score, and that overestimators tend to be less likely to engage in positive financial behaviors (such as budgeting or regular savings). In contrast, Levinger et al. (2011) find that a substantial proportion of LMI consumers who visit free tax preparation sites underestimate their credit scores, and that this underestimation is associated with more costly loan terms, such as higher interest rates on credit cards. Levinger et al. (2011) suggest that such consumers may view themselves as more borrowing-constrained than they actually are, and thus do not pursue more affordable financing options. While each of these studies suggests an association between biased self-assessments and financial behaviors, they do not directly consider the relationship between debt perceptions and debt acquired, such as through home purchase.

In addition to analyzing the amount of debt acquired through purchase, our study considers how debt estimations influence whether or not consumers accept offers of financial coaching after purchase. Given the complexities of the home purchase process and the responsibilities of new homeowners, homebuyer education and counseling has been promoted as a tool to increase mortgage access and reduce mortgage default since the early 1970s (McCarthy and Quercia 2000), with limited evidence of effectiveness (e.g., Agarwal et al. 2009; Avila, Nguyen, and Zorn 2013; Carswell, James, and Mimura 2009; Hirad and Zorn 2002). Historically, emphasis has been placed on pre-purchase education and counseling, where education provides *information* about the home buying process (e.g., selecting a home, understanding financing, closing documents) and counseling provides *individualized assistance* to address specific barriers to home purchase (e.g., credit report repair, securing affordable financing)

(Collins and O'Rourke 2010; Moulton 2012). There has also been some emphasis on homeowner counseling post-purchase, but this counseling focuses primarily on helping distressed homeowners at risk of foreclosure with mortgage renegotiation or financial assistance (Collins 2007; Collins and Schmeiser 2013; Ding, Quercia, and Ratcliff 2008).

In contrast to more traditional methods of education and counseling, financial coaching is future-oriented and self-directed, and focuses on working with consumers in collaboration to achieve predetermined goals (Bluckert 2005). In a homeownership context, coaching includes helping consumers set and monitor progress toward financial goals after home purchase, including but not limited to meeting their new monthly mortgage obligation and home maintenance expenses. While financial coaching is relatively new, it draws from a broader coaching field in psychology that incorporates external monitoring to help with self-control problems or with the degree to which people can restrain impulses (Biswas-Diener and Dean 2007; Grant 2008). Preliminary evidence suggests that financial coaching may lead to sustained behavioral change and thus goal attainment (Baumeister 2002; Baumeister et al. 2008; Collins, Baker, and Gorey 2007). Coaching has also been effective in other fields, such as healthcare (Hayes and Kalmakis 2007; Tidwell et al. 2004).

One of the challenges with evaluating the effectiveness of education, counseling, and coaching strategies is self-selection. Most services for new homeowners are voluntary, and there is reason to believe that those who need coaching 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 (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 positive associations between counseling-related interventions and mortgage outcomes does not account for this potential bias (Hung and Yoong 2010; Quercia and Ding 2009; Rademacher et al. 2010).

This study adds to the literature on biased self-assessment and financial decision-making by examining the association between self-assessments of borrowing capacity and financial behaviors related to home purchase. The following key questions are explored in this study:

1. To what extent do LMI homebuyers accurately estimate their overall borrowing capacity? On the basis of related research, our

proposition is that a significant number of LMI homebuyers under- or overestimate their total amount of debt and the amount of their monthly debt payments.

2. How does the accuracy of estimates influence decisions regarding mortgage debt? On the basis of related research, our proposition is that those who underestimate monthly debt payments are more likely to take out larger mortgages, relative to income, and have higher mortgage payments compared to LMI homebuyers who correctly estimate or underestimate their debt burdens.
3. Which factors influence the take-up of the offer of free financial coaching among LMI recent homebuyers? On the basis of related research, our proposition is that underestimation of debt and monthly debt payments as well as overconfidence in meeting debt repayment obligations reduce the interest in financial coaching.

DATA AND METHODS

Study Population

We examine our key research questions using baseline data collected as part of a 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. The program serves individuals with household incomes below 115% of area median income, or up to 140% of median income in federally designated underserved target areas. In OHFA's program, mortgages are originated through a network of participating private lenders (i.e., banks or mortgage companies). After prospective borrowers are approved for financing with an originating lender, they are required to complete an online homebuyer education course on OHFA's website. Homebuyers completing the online education through this course from May 20, 2011 through December 31, 2011 completed an additional online financial assessment (called "MyMoneyPath"). Upon completion of the assessment, prospective homebuyers were invited to participate in the study following an IRB-approved protocol. Homebuyers who agreed to participate received a $25 Amazon.com gift card via e mail. Approximately two-thirds of the prospective homebuyers recruited (573, or 62%) consented to participate in the study. At the conclusion of the initial data collection period (June 30, 2012), 488 (85%) of the consenting participants purchased a home. Those not purchasing a home through OHFA's program were not included in the study, as administrative credit and mortgage data linked to the self-assessment is only available for OHFA-funded borrowers. A total of 420 of these homebuyers had complete credit report and mortgage-origination data and are the basis of the sample for our study. As part of the intervention, about two thirds of homebuyers were randomized to receive an offer of telephone-based financial coaching, and about one third of those consumers took up the offer. The phone-based financial coaching offer was made after the completion of the financial assessment and post home purchase. The randomly selected homebuyers were contacted by a mailed letter, an email follow-up, and then a phone call from the coach offering this free service. If accepted, the coaching consisted of an initial hour-long phone session to review the results of the financial assessment and acquaint the homebuyer with the coach, followed by four quarterly phone sessions to monitor goal progress and provide support. The coaching was conducted by trained financial counselors who were employed at a local housing counseling agency. Three coaches were employed for the study, and were randomly assigned to participants as participants completed the enrollment process.

Data Sources

Our study combines self-reported indicators of financial health from the online financial assessment, credit report, mortgage loan application, and mortgage-origination data. Appendix 1 provides the descriptions of all variables used in our analysis. The data collected at the time of loan application includes basic demographic information about the borrower, such as household income, household composition, and occupation. The data collected at mortgage origination includes some demographic information; characteristics of the mortgage transaction, such as mortgage amount, appraised value, and monthly payment (principal, interest, taxes and insurance); and credit report data collected shortly after home purchase. 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). The narrow time frame in which self-reported and credit report, mortgage loan application, and mortgage-origination data are collected provides a useful snapshot of a household's actual and perceived financial situation around the same point in time.

Model Variables

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 influences the amount of mortgage debt they acquire through home purchase as well as participation in a free offer of financial coaching. We hypothesize that these decisions are directly related to the extent to which the LMI consumer accurately estimates his or her borrowing capacity.

The assessment that consumers complete as part of the study also contains questions about other common indicators of financial capability. Therefore, we further investigate the extent to which other common indicators of financial capability predict mortgage consumption. Finally, we investigate the extent to which common indicators of financial capability are associated with over- and underestimation of total debt and overconfidence toward debt repayment.

Borrowing Capacity

We include two types of measures for borrowing capacity: (1) amount of nonmortgage debt (total and monthly payments) and (2) debt repayment history. First, we construct indicators for agency-reported debt from participant credit reports obtained shortly after loan closing. To calculate the agency-reported total debt and monthly debt payments, we sum the total outstanding balance and minimum monthly payments for revolving and nonmortgage installment debt from the credit reports. Average total nonmortgage agency-reported debt is $27,932, with a minimum monthly payment of $469 (see Table 1). In our empirical specifications, we control for the total nonmortgage, agency-reported debt as total debt (logged) and as a percent of household monthly income (DTI administrative). The measure of household monthly income is taken from the mortgage application data verified by the Ohio Housing Finance Agency.[1] We expect that a higher total debt and nonmortgage DTI will be associated with lower mortgage amounts, on average, as consumers with more nonmortgage debt have less capacity for additional borrowing. We also expect that consumers with greater total debt will be more

1. The Ohio Housing Finance Agency verifies income to qualify households for the mortgage program. All household income is included in the calculation, including household members not listed as borrowers on the mortgage. Income verified by the bank includes only borrower income, and is thus lower than the OHFA household income. We include a control variable for the difference between household income and borrower verified income.

TABLE 1
Debt Characteristics and Estimation Accuracy

	Mean	SD	Minimum	Maximum
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
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
Estimation accuracy				
Overconfidence	14.3%		0	1
Nonreport debt	8.8%		0	1
Total debt underestimate ≤\$5,000	31.5%		0	1
Total debt overestimate >\$2,000	11.5%		0	1
Monthly debt payments				
Over, difference >\$100	11.7%		0	1
Over, difference >\$0 and <\$100	27.4%		0	1
Under, difference <\$0 and ≥\$100	33.0%		0	1
Under, difference ≤\$100 and ≥\$200	10.8%		0	1
Under, difference ≤\$200 and ≥\$400	8.2%		0	1
Under, difference ≤\$400	8.9%		0	1

Note: $N = 422$.

likely to underestimate their debt, as they have a larger margin for error.

Measures of under- and overestimation of debt are constructed from 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 to estimate the minimum monthly payment and total outstanding balance for each source of debt. On average, participants self-report \$21,743 in total nonmortgage debt, with minimum monthly payments of \$402. Comparing self-reported debt to agency-reported debt, respondents underestimate their debt by \$6,189 on average. For the empirical analysis, we code those self-reporting total debt that is \$5,000 or more lower than the agency-reported total debt as under-estimators (31.5% of study participants). \$5,000 is about the mean difference between self-reported and agency-reported debt. We code those reporting total debt that is \$2,000 or more greater than agency debt as overestimators, representing 11.5% of our sample. Our threshold for overestimators is lower than our threshold for underestimators, as the distribution is skewed to the left with very few households overestimating their debt by $5,000 or more. This result may be explained by the concept of loss aversion. Loss aversion describes the tendency of individuals to be disproportionately averse to incurring losses as compared to acquiring gains, relative to a reference point (Kahneman and Tversky 1979). Thus, in this study, loss-averse individuals are more likely to misestimate in the direction of lower debt.

We also include an indicator for respondents who do not self-report any debt ("Nonreport Debt"), even though they have $1,000 or more in total debt on their credit report (8.8%). We assume that respondents who do not report any debt either did not want to provide this information or they considered themselves debt-free at the time of data collection.

To supplement our measures based on estimation of *total* debt, we include measures for estimation of monthly debt payments. Because minimum monthly payments are "lumpy," we expect that differences in monthly payment amounts may be nonlinear. We thus develop six categorical variables for estimated to actual monthly debt payments based on the distribution of the data, the first four of which indicate those who underestimate monthly debt: (1) underestimate by $0–$100 (33%); (2) underestimate by $100–$200 (10.8%); (3) underestimate by $200–$400 (8.2%); and (4) underestimate by greater than $400 (8.9%). To measure overestimation of monthly debt payments, we constructed two additional categories: (5) overestimate by $0 to $100, our reference category in the regression analysis (27.4%); and (6) overestimate by more than $100 (11.7%). While we include both installment and revolving debt payments in our primary specification, in alternative specifications we include each separately and find that our results are robust.

Overconfidence

Another component of borrowing capacity is the ability to repay debt. From the credit report data, we include an indicator for whether or not the consumer has a loan or credit card payment that was 60 or more days delinquent within the last 24 months, indicating that the consumer has recently struggled to repay their debt, representing 21.2% of our sample. However, some consumers who appear to be struggling with debt repayment (as indicated by their credit report) may not perceive themselves to have difficulty with debt, for a variety of possible reasons. These borrowers may simply not pay attention to their payments, they may be strategically defaulting on payments, or they may have had a negative payment shock in the past and are now more diligent at repayments than before. Regardless of the mechanism, we predict that these incongruent consumers will exhibit biased behaviors relative to mortgage borrowing. To construct a measure of this behavior, we combine the indicator for delinquencies in the last 24 months with an indicator for self-reported confidence in "paying off debt." Specifically, those who self-reported they are "very confident" paying off debt ("4"), but also have a transaction that was 60 or more days delinquent within the last 24 months are coded "1," representing 14.3% of participants in our sample (see Table 1).

Mortgage Consumption

In our second set of analyses, we estimate models to predict mortgage consumption. In line with other studies (Quercia, McCarthy, and Wachter 2003), we measure mortgage consumption in two ways: (1) as the dollar amount of the monthly mortgage payment, and (2) 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 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 shown in Table 2, 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% (ranging from 7.7% to 51.6%).

Propensity to Take-Up Financial Coaching

About one-third (107 or 37.8%) 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 coaching and completed at least one session, and about 19% completed all coaching sessions. The descriptive statistics presented in Table 2 show that those who underestimate their total debt by $5,000 or more take-up coaching at approximately the same rate as those who do not underestimate

TABLE 2
Descriptive Statistics

	Full Sample				Underestimate Total Debt $5,000 or more		Overconfident	
	Mean	SD	Min	Max	No	Yes	No	Yes
Dependent variables								
Front-end ratio	22.6%	6.9%	7.7%	51.6%	22.4%	23.1%	22.3%	24.4%**
Mortgage payment	$815	$249	$266	$1,713	$793	$876**	$806	$869^
Take-up coaching	37.8%	0.49%	0	1	38.8%	35.4%	40.8%	20.9%*
Borrowing capacity								
DTI administrative	11.1%	8.1%	0.0%	78.6%	11.1%	17.7%**	12.5%	15.1%*
Total debt (hundreds; logged)	9.50	1.81	0	11.72	9.09	10.61**	9.44	9.88^
Missed debt payments	21.3%	41.0%	0	1	18.9%	26.7%^	8.0%	100.0%**
Financial capability indicators								
Financial literacy	1.61	0.59	0	2	1.65	1.50**	1.63	1.50^
Professional advice	14.5%	35.3%	0	1	14.0%	15.9%	14.4%	15.0%
Future discounting	8.6%	0.28%	0	1	5.9%	15.9%**	8.3%	10.0%
Financial confidence	17.89	1.91	10	20	17.86	17.96	17.81	18.35*
Control variables								
Credit score	668.29	50.36	495	795	671.80	658.73**	673.87	634.80**
Monthly income (hundreds)	37.70	12.08	8.43	70.01	36.91	39.87*	37.88	36.64
Household income difference (hundreds)	4.31	10.15	−82.02	39.97	4.40	4.09	4.74	1.77*
Amount saved (hundreds, logged)	5.54	3.63	0.00	10.11	5.61	5.36	5.56	5.42
Female	46.0%	49.9%	0	1	44.6%	49.6%	45.8%	46.7%
Borrower age	32.77	10.17	20	89	33.19	31.62	33.01	31.33
Education college	35.2%	47.8%	0	1	31.6%	45.1%*	35.3%	35.0%
Minority	14.3%	35.0%	0	1	11.7%	21.2%*	13.1%	21.7%^
Household size	2.44	1.30	1	7	2.39	2.58	2.44	2.47
Days to credit data (logged)	4.43	0.33	2.08	5.73	4.43	4.45	4.43	4.43

^$p < 0.10$, *$p < 0.05$, **$p < 0.01$ (based on t-test for means and Chi-square test for proportions).

their total debt (38.8% compared with 35.4%) However, those who are overconfident are half as likely to taking up coaching, with 20.9% of those who are overconfident taking up coaching, compared with 40.8% of those who are not overconfident. We employ a logistic regression model with take-up of financial coaching as the binary outcome variables.

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 questions measuring financial literacy taken from Lusardi and Tufano (2009) (see Appendix 1 for questions). 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% of our sample.

Third, the self-assessment includes five questions related to confidence with managing the following financial activities: day-to-day finances, paying off debt, making a mortgage payment, planning for future expenses, and planning for retirement. 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% 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). First, financial indicators include the 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 (coded as 1 if 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).

FINDINGS

Estimation of Biased Perceptions

Almost one-third of study participants underestimate the total amount of household debt by $5,000 or more; one in 10 overestimate their household debt by $2,000 or more. In addition, one in seven express overconfidence in debt repayment. Our first set of analyses, presented in Table 3, determines the predictors of these misperceptions. Underestimation of total household debt by $5,000 or more is, as expected, associated with higher total debt (an increase in total debt is associated with the likelihood of underestimation), higher incidence of nonreporting of debt, and lower credit scores. In addition, lower financial literacy, higher future discount rates, and not being labeled as "overconfident" are positively correlated with underestimation of total household debt. Overestimation of debt of $2,000 or more is associated with lower incidence of nonreported debt, higher overall financial confidence, and being labeled "overconfident." In addition, college-educated respondents are more likely to overestimate their debt.

Our measure of overconfidence reflects those who appear to be struggling with debt repayment (as indicated by their credit report) but do not perceive themselves to have difficulty with debt. It is a composite measure of those who self-reported they are "very confident" paying off debt ("4"), but also have a transaction that was 60 or more days delinquent within the last 24 months. Membership in this group of incongruent consumers is associated with a lower credit score, lower

TABLE 3
Binomial Logistic Regressions Predicting Biased Perceptions

	(1) Underestimate Total Debt			(2) Overestimate Total Debt			(3) Overconfidence		
	β	Robust SE	Δ Pr[a]	β	Robust SE	Δ Pr[a]	β	Robust SE	Δ Pr[a]
DTI administrative	2.254	1.734	2.34%	−0.826	1.987	−0.57%	1.252	2.473	1.29%
Total debt (logged)	2.028	0.260	46.05%**	−0.051	0.093	−0.70%	0.282	0.307	5.78%
Missed payment in 24 months	0.261	0.570	3.26%	−1.007	0.835	−5.07%			
Total debt underestimate ≤$5,000							−0.630	0.457	−5.62%
Total debt overestimate >$2,000							0.405	0.511	3.93%
Nonreport debt	1.807	0.485	34.73%**	−1.395	0.676	−6.07%*	0.613	0.501	8.61%
Overconfidence	−1.355	0.650	−9.34%*	1.638	0.882	23.38%^			
Financial literacy	−0.510	0.240	−3.44%*	0.235	0.289	1.06%	−0.262	0.245	−1.76%
Professional advice	−0.058	0.413	−0.65%	0.505	0.406	4.72%	−0.069	0.495	−0.76%
Future discounting	0.867	0.423	13.29%*	0.203	0.550	1.67%	0.354	0.456	4.55%
Financial confidence	0.060	0.089	1.30%	−0.141	0.085	−2.04%^	0.209	0.095	4.53%*
Credit score	−0.012	0.003	−6.74%**	0.003	0.004	0.97%	−0.023	0.004	−13.45%**
Monthly income (hundreds)	−0.019	0.015	−2.69%	0.009	0.018	0.80%	0.007	0.019	0.93%
Household income difference	0.001	0.014	0.15%	0.024	0.022	1.90%	−0.051	0.030	−5.88%^
Amount saved (logged)	−0.040	0.038	−1.66%	0.047	0.044	1.30%	−0.048	0.046	−1.96%
Female	−0.325	0.288	−3.27%	−0.454	0.358	−2.85%	0.023	0.321	0.26%
Borrower age	0.009	0.015	1.06%	0.011	0.021	0.81%	−0.041	0.015	−4.70%**
Education college	−0.425	0.374	−4.12%	1.060	0.423	12.36%*	0.022	0.454	0.25%
Minority	0.392	0.424	5.13%	−0.364	0.550	−2.37%	0.093	0.405	1.08%
Household size	0.164	0.120	2.41%	0.236	0.134	2.32%^	−0.043	0.121	−0.64%
Days to credit data (logged)	0.337	0.536	1.26%	0.798	0.484	2.00%^	−0.407	0.512	−1.52%
Constant	−15.1	4.081	**	−6.532	4.207		10.56	4.904	*
Base Pr (Y)			13.07%			8.25%			12.98%
Pseudo R-Squared	0.366**			0.105**			0.193**		

Note: $N = 420$; Logistic regression models with robust standard errors.
[a]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.
$^{\wedge}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

borrower age, higher overall financial confidence, and lower household incomes.

Borrowing Capacity and Mortgage Consumption

To explore the relationship between perceived and actual borrowing capacity and mortgage debt, we first estimate a series of OLS models with the full monthly mortgage payment as the dependent variable (Table 4, columns 1 and 2), and then the front-end ratio as the dependent variable (Table 4, columns 3 and 4). To measure borrowing capacity, we first include the dummy variables for over- and underestimation of total debt (columns 1 and 3), and then include the categorical measures for monthly payment estimation (columns 2 and 4).

First, as would be expected, an increase in monthly DTI is significantly associated with a decrease in mortgage payment and the front-end ratio across all specifications, highlighting the importance of nonmortgage borrowing capacity for mortgage consumption. We also find evidence that underestimation of total debt by \$5,000 or more is significantly associated with increased mortgage consumption. Specifically, those who underestimate their total nonmortgage debt by \$5,000 or more have monthly mortgage payments that are about \$41 higher and front-end ratios that are 1.6% higher on average, holding constant other model variables. Further breaking down the underestimation by monthly payment categories, we find that an increase in the amount of payment underestimation is associated with an increase in both mortgage payment and the front-end ratio. Specifically, those who underestimate their monthly payments by \$200–\$400 have monthly mortgage payments that are \$76 higher and front-end ratios that are 1.8% higher, on average, than those who do not underestimate or significantly overestimate their debt (the reference category). Those who underestimate their monthly debt payments by \$400 or more have monthly mortgage payments that are \$153 higher and front-end ratios that are 4.3% higher, on average, than those who accurately estimate their monthly debt (the reference category). Finally, nonreporters (who do not self-report any debt even though they have at least \$1,000 in debt on their credit report) have significantly higher mortgage payments and front-end ratios on average (\$67 and 2.0%, respectively), than those who report their debt.

We do not find that overconfidence is significantly associated with higher mortgage debt, after controlling for other model covariates. Other indicators of financial capability, including indicators for financial

TABLE 4
OLS Regressions Predicting Mortgage Debt

	(1) Mortgage Payment		(2) Mortgage Payment		(3) Front-End Ratio		(4) Front-End Ratio	
	β	Robust SE	β	Robust SE	β	Robust SE	β	Robust SE
DTI administrative	−437.500**	130.400	−744.100**	143.100	−0.140*	0.065	−0.217**	0.068
Total debt (logged)	2.001	7.210	7.943	7.174	0.001	0.002	0.003	0.002
Missed payment in 24 months	16.310	42.170	0.909	39.480	0.004	0.012	−0.001	0.011
Total debt underestimate ≤\$5,000	41.410^	25.130			0.016*	0.007		
Total debt overestimate >\$2,000	−34.130	29.620			−0.003	0.008		
Over payment >\$100			−74.370*	32.440			−0.021*	0.010
Under payment <\$0 and ≥\$100			27.810	23.940			0.009	0.007
Under payment ≤\$100 and ≥\$200			56.250	43.220			0.012	0.012
Under payment ≤\$200 and ≥\$400			75.590^	40.830			0.018^	0.011
Under payment ≤\$400			153.200**	46.430			0.043**	0.014
Nonreport debt	66.690*	29.800	40.770	30.970	0.020^	0.010	0.014	0.011
Overconfidence	40.660	51.010	52.610	48.440	0.010	0.015	0.013	0.014
Financial literacy	23.470	17.070	19.450	16.870	0.007	0.005	0.006	0.005
Professional advice	4.404	29.270	5.562	29.430	0.000	0.009	0.001	0.009
Future discounting	−23.620	32.500	−12.640	31.320	−0.002	0.010	0.001	0.009
Financial confidence	2.109	5.772	0.571	5.726	0.001	0.002	0.001	0.002
Credit score	0.019	0.215	−0.078	0.211	0.000	0.000	0.000	0.000
Monthly income (hundreds)	12.420**	1.054	12.490**	1.046	−0.003**	0.000	−0.003**	0.000
Household income difference	−7.533**	1.683	−8.256**	1.543	−0.001	0.001	−0.001	0.001
Amount saved (logged)	0.681	2.800	−0.546	2.759	0.001	0.001	0.000	0.001
Female	0.888	20.700	−0.605	20.300	0.001	0.006	0.001	0.006
Borrower age	−0.580	0.992	−0.728	1.013	0.000	0.000	0.000	0.000
Education college	49.970*	24.200	54.420*	24.030	0.012^	0.007	0.014*	0.007
Minority	96.350**	31.930	79.640*	31.030	0.025**	0.009	0.020*	0.008
Household size	8.407	8.767	7.425	8.639	0.001	0.002	0.001	0.002
Days to credit data (logged)	−18.100	28.820	−24.390	27.470	−0.002	0.009	−0.003	0.009
Constant	345.900	225.900	458.200*	224.900	0.311**	0.069	0.339**	0.068
R-Squared	0.412**		0.437**		0.343**		0.366**	

Note: $N = 422$; OLS with robust standard errors.
^$p < 0.10$, *$p < 0.05$, **$p < 0.01$.

literacy, financial confidence, future discounting, and credit, are not significantly associated with the amount of mortgage debt.

Not surprisingly, we find that income is significantly associated with a higher monthly housing payment and lower front-end ratio. 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. Controlling for other model covariates, minority borrowers and borrowers with a college degree tend to have higher mortgage payments and front-end ratios.

Predicting Take-Up of Financial Coaching

Next, we estimate two binary logistic regression models to predict take-up of the offer for free financial coaching after home purchase, starting with the dummy variable for over and underestimating debt (Table 5, column 1) and then with the categorical measures for monthly payment differences (column 2). While total debt over- and underestimation is not significantly associated with take-up of coaching, monthly debt estimation is associated with take-up. Specifically, those who overestimate their monthly debt payments by \$100 or more are more likely (19.3%) to take-up the offer of free financial coaching. In addition, those who underestimate their monthly debt payments by \$100–\$200 or \$400 or more are also more likely to participate in financial coaching, (by 17.5% and 26.7%, respectively), than those who do not underestimate their monthly debt payment.

We also find a significant relationship between our measure for overconfidence and the probability of taking up financial coaching. Those who are overconfident in their ability to pay off their debt are significantly less likely (22.8%) to take-up the offer of financial coaching in both model specifications. In contrast, consumers who have a tradeline that is 60 or more days delinquent within the last 24 months but are not overconfident are more likely (22.9%) to take-up financial coaching. Interestingly, an increase in overall financial confidence, a composite of five questions on dimensions of financial confidence, is related to an increased likelihood of participation in financial coaching in both model specifications.

TABLE 5
Binomial Logistic Regressions Predicting Take-Up of Financial Coaching

	(1)			(2)		
	β	Robust SE	Δ Pr[a]	β	Robust SE	Δ Pr[a]
DTI administrative	−2.404	2.012	−4.70%	−5.143	2.669	−6.18%^
Total debt (logged)	0.028	0.131	1.04%	0.037	0.136	0.83%
Missed payment in 24 months	0.985	0.613	22.94%^	0.945	0.610	15.75%
Total debt underestimate ≤$5,000	0.026	0.360	0.53%			
Total debt overestimate >$2,000	0.545	0.465	9.52%			
Over payment >$100				1.123	0.480	19.63%*
Under payment <$0 and ≥$100				−0.157	0.362	−1.83%
Under payment ≤$100 and ≥$200				1.030	0.562	17.57%^
Under payment ≤$200 and ≥$400				0.236	0.669	3.14%
Under payment ≤$400				1.426	0.697	26.72%*
Nonreport debt	−0.100	0.420	−1.95%	−0.418	0.419	−4.41%
Overconfidence	−2.018	0.701	−22.84%**	−1.965	0.704	−12.04%**
Financial literacy	−0.122	0.246	−1.47%	−0.148	0.246	−1.10%
Professional advice	−0.335	0.424	−6.19%	−0.247	0.429	−2.77%
Future discounting	−0.570	0.499	−9.88%	−0.470	0.538	−4.87%
Financial confidence	0.166	0.086	6.39%^	0.208	0.092	4.93%*
Credit score	0.004	0.003	3.88%	0.005	0.004	2.68%
Monthly income (hundreds)	−0.002	0.015	−0.61%	−0.005	0.017	−0.80%
Household income difference	−0.017	0.017	−3.32%	−0.019	0.018	−2.31%
Amount saved (logged)	−0.060	0.042	−4.45%	−0.070	0.043	−3.21%^
Female	0.668	0.281	15.06%*	0.698	0.290	10.83%*
Borrower age	−0.005	0.015	−0.98%	−0.006	0.014	−0.72%
Education college	−0.043	0.358	−0.84%	−0.076	0.368	−0.91%
Minority	0.555	0.436	12.33%	0.441	0.426	6.30%
Household size	0.079	0.115	2.05%	0.063	0.119	1.00%
Days to credit data (logged)	−0.330	0.429	−2.15%	−0.481	0.434	−1.92%
Coach_1	1.218	0.403	28.73%**	1.337	0.412	24.58%**
Coach_2	0.069	0.400	1.41%	−0.049	0.433	−0.59%
Coach_3	1.496	0.404	35.40%**	1.605	0.414	31.10%**
Constant	−4.992	3.783		−5.142	3.949	
Pseudo R-Squared	0.133**			0.1654		
Base Pr (Y)			27.68%			14.33%

Note: $N = 283$; Logistic regression model with robust standard errors.
[a]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.
^$p < 0.10$, *$p < 0.05$, **$p < 0.01$.

In addition to financial measures, gender is significantly associated with coaching, where females are more likely to take-up coaching (15.0%). There are also differences in take-up by assigned financial coach. Four financial coaches were employed as part of the study and randomly paired with participants in the treatment group to make the offer of financial coaching. We find significant differences in take-up rates by financial coach offering the coaching, 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 coaching.

CONCLUSIONS

Using a unique sample of consumers that includes both self-reported and administrative data, our analysis provides evidence that perceptions of borrowing capacity are an important, unique component of LMI consumer mortgage decisions. First, we present factors that influence recent LMI homebuyers' perception of their household debt and contribute to overconfidence in repaying debt. Next, we document a relationship between inaccurate estimations of debt and consumer behavior, in this case, mortgage consumption. One of the concerns in the literature is that there may be systematic variation in the financial behaviors of those who accurately or inaccurately estimate their financial situation (Zinman 2009). In terms of under- or overestimating debt, we find preliminary evidence that inaccuracies may be associated with mortgage consumption behaviors. In particular, those who underestimate their total or monthly nonmortgage debt systematically consume more mortgage debt relative to those who accurately estimate their debt. In the next paragraphs, we discuss potential avenues for future research that may prove useful in better understanding the mechanisms that underlie these financial decisions.

Accuracy of Debt Estimates

In the current research, we do not observe why consumers under- or overestimate their debt relative to the debt reported on credit report files. We assume that the debt reported on the credit file is more accurate than self-reported debt, but it may well be that consumers actually possess more complete information about their own debt. There is some evidence that information reported on credit report files may possess errors. For example, accounts may be listed twice, balances may be inaccurate, or certain accounts may be omitted (Avery, Brevoort, and Canner 2009; Avery, Calem, and Canner 2004). To the extent that borrowers have more complete information, they may use this information when making financial decisions. To test for this alternative explanation, we substituted credit report data with data provided by the mortgage underwriter on monthly debt payments, and find that our results are robust. Future research may address this issue also by inquiring about study participants' confidence in their financial estimates, as suggested in cognitive question testing methods (Collins 2003; Gigerenzer 1991).

Financial Conscientiousness

While this study is limited to low-to-moderate income recent homebuyers, our findings on debt misestimation and mortgage behaviors have significant policy implications. The evidence reported here supports the notion that financial conscientiousness, a term referring to a "consumer regularly attending to financial matters in an organized, orderly and precise manner" (Bone 2008, 176), may be important for making informed financial decisions. To the extent that the borrower consumes more "house" 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. The implications are twofold. First, a potentially important role for pre-purchase homebuyer interventions is not only to increase financial literacy, but also to increase the consumer's awareness of his/her own financial situation. A recent study indicates that personalized advice that directs lower-income homeowners' attention to future needs, rather than generic educational literature may be most effective in meeting this need (Shah, Mullainathan, and Shafir 2012). 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 situations (e.g., Servon and Kaestner 2008).

Second, this study highlights the importance of early intervention in the home purchase process. Interventions may be less effective for changing borrower decisions after LMI homebuyers have signed a purchase offer, as was the case in the current study. However, earlier interventions may be challenging to implement because programs that require homebuyer education and counseling may not interact with the borrower until after he or she has an offer and is being approved for financing. Federal and state mortgage programs requiring education and counseling should consider strategies to engage homebuyers much earlier in the process. We propose that agents that have earlier contact with prospective homebuyers, such as realtors, may provide a more timely moment of intervention. Of course, steps must be taken to align the incentives of agents with those of homebuyers. In response to the mortgage crisis, policies that require homebuyer education and counseling for certain LMI homebuyers are being considered. However, interventions offered as a one-time shot immediately prior to purchase, after critical decisions regarding the purchase have already been made, may have little to no impact on desired mortgage outcomes.

Financial Coaching and Overconfidence

Our study also sheds light on factors that predict take-up of financial coaching. Building on Meier and Sprenger (in press), we 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 coaching. Our findings contribute to the growing literature on the relationship between need and take-up of counseling or coaching services (Hung and Yoong 2010; Meier and Sprenger 2007, in press). On the one hand, the finding that borrowers who have a history of missed payments are more likely to take-up coaching suggests positive self-selection of those who are in greater need of information and support. On the other hand, the finding that overconfidence in debt repayment predicts lower take-up of coaching suggests that those who have difficulty in repayment, but are unaware of it, do not respond in the desired manner. Thus, future research should consider the role of high confidence in debt-related decisions, an issue which appears to have been limited to investment trading and retirement literacy (Barber and Odean 2001; Rooij, Lusardi, and Alessie 2011). Work by Ülkümen et al. (2008) is an exception, though this work is limited to budgeting estimates.

In conclusion, this research provides insights into the biases in the information that consumers use to make financial decisions, relative to the administrative data that firms use. The bad news is that underestimation of nonmortgage debt is a significant predictor of taking out a larger mortgage, potentially putting the consumer at a higher risk of default. The good news is that those who misestimate their nonmortgage debt are also more likely to take-up an offer of financial coaching. The study thus begs the question: can the new interactive technologies be used at scale to personalize financial education, and will this de-bias consumers and reduce the amount of mortgage debt they take on? While our study does not provide a causal conclusion, we hope that the present research encourages others to explore this intriguing area through randomized intervention studies.

APPENDIX 1: Variable Descriptions

Variable Name	Description
Administrative DTI	Administrative Debt to Income (DTI) ratio, verified monthly debt/household monthly income
Total debt (logged)	Total nonmortgage household debt
Missed payment in 24 months	Consumer has a transaction that was 60 or more days delinquent within the last 24 months
Total debt underestimate $\leq$\$5,000	Coded “1” if the borrower underestimates his/her total nonmortgage debt by \$5,000 or more
Total debt overestimate >\$2,000	Coded “1” if the borrower overestimates his/her total nonmortgage debt by \$2,000 or more.
Over payment >\$100	Coded “1” if the borrower overestimates his/her nonmortgage monthly debt payments by \$100 or more
Under payment <\$0 and $\geq$\$100	Coded “1” if the borrower underestimates his/her nonmortgage monthly debt payments by \$0 to \$100
Under payment $\leq$\$100 and $\geq$\$200	Coded “1” if the borrower underestimates his/her nonmortgage monthly debt payments by \$100 to \$200
Under payment $\leq$\$200 and $\geq$\$400	Coded “1” if the borrower underestimates his/her nonmortgage monthly debt payments by \$200 to \$400
Under payment $\leq$\$400	Coded “1” if the borrower underestimates his/her nonmortgage monthly debt payments by more than \$400
Nonreport Debt	Coded “1” if the borrower reports that they do not have debt when they have more than \$2,000 in debt listed on their credit report file
Overconfidence	Coded 0-1, where code=1 if the borrower was ever delinquent on a transaction on their credit report within the last 24 months, and borrower self-rated their confidence with “paying off debt” as “very confident.”
Financial literacy	Summative score ranging from 0 to 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; I don’t know
Inflation literacy	Imagine that the interest rate on your savings account was 1% per year and 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; I don’t know
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.”

APPENDIX 1: Continued

Variable Name	Description
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).
Credit score	Median credit score from credit report file
Monthly income (hundreds)	Monthly household income (hundreds), 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

REFERENCES

Acquaye, Lucy. 2011. Low-income Homeowners and the Challenges of Home Maintenance. *Community Development*, 42 (1): 16–33.

Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, and Douglas D. Evanoff. 2009. Do Financial Counseling Mandates Improve Mortgage Choice and Performance? Evidence from a Legislative Experiment, Working Paper No. 2009-07. Federal Reserve Bank of Chicago.

Ambrose, Brent W. and Charles A. Capone. 1998. Modeling the Conditional Probability of Foreclosure in the Context of Single-family Mortgage Default Resolutions. *Real Estate Economics*, 26 (3): 391–429.

Ashraf, Nava, Dean S. Karlan, and Wesley Yin. 2005. Tying Odysseus to the Mast: Evidence from a Commitment Savings Product in the Philippines. *Quarterly Journal of Economics*, 121: 635–672.

Avery, Robert B., Paul S. Calem, and Glenn B. Canner. 2004. Credit Report Accuracy and Access to Credit. *Federal Reserve Bulletin*, 90 (3): 297–322.

Avery, Robert B., Kenneth P. Brevoort, and Glenn B. Canner. 2009. Credit Scoring and Its Effects on the Availability and Affordability of Credit. *Journal of Consumer Affairs*, 43 (3): 516–537.

Avila, Gabriela, Hoa Nguyen, and Peter Zorn. 2013. The Benefits of Pre-purchase Homeownership Counseling, Working Paper (April 2013). McLean, VA: Freddie Mac, Models, Mission and Research Division.

Barber, Brad M. and Terrance Odean. 2001. Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment. *The Quarterly Journal of Economics*, 116 (1): 261–292.

Baumeister, Roy F. 2002. Yielding to Temptation: Self-control Failure, Impulsive Purchasing, and Consumer Behavior. *Journal of Consumer Research*, 28 (March): 670–676.

Baumeister, Roy F., Erin A. Sparks, Tyler F. Stillman, and Kathleen D. Vohs. 2008. Free Will in Consumer Behavior: Self-control, Ego Depletion, and Choice. *Journal of Consumer Psychology*, 18 (1): 4–13.

Benzion, Yuri, Amnon Rapoport, and Joseph Yagil. 1989. Discount Rates Inferred from Decisions: An Experimental Study. *Management Science*, 35: 270–284.

Biswas-Diener, Robert and Ben Dean. 2007. *Positive Psychology Coaching: Putting the Science of Happiness to Work for Your Clients*. Hoboken, NJ: John Wiley.

Bluckert, Peter. 2005. The Similarities and Differences between Coaching and Therapy. *Industrial and Commercial Training*, 37 (2): 91–96.

Boehm, Thomas P. and Alan M. Schlottmann. 1999. Does Home Ownership by Parents Have an Economic Impact on Their Children? *Journal of Housing Economics*, 8 (September): 217–232.

Bone, Paula Fitzgerald. 2008. Toward a General Model of Consumer Empowerment and Welfare in Financial Markets with an Application to Mortgage Servicers. *Journal of Consumer Affairs*, 42 (2): 165–188.

Bricker, Jesse, Brian Bucks, Arthur Kennickell, Traci Mach, and Kevin Moore. 2012. The Financial Crisis from the Family's Perspective: Evidence from the 2007–2009 SCF Panel. *Journal of Consumer Affairs*, 46 (3): 537–555.

Bucks, Brian and Karen Pence. 2008. Do Borrowers Know Their Mortgage Terms? *Journal of Urban Economics*, 64 (2): 218–233.

Carswell, Andrew T., Russell N. James, and Yoko Mimura. 2009. Examining the Connection between Housing Counseling Practices and Long-term Housing and Neighborhood Satisfaction. *Community Development*, 40 (1): 37–53.

Chan, Sewin and Ann Huff Stevens. 2008. What You Don't Know Can't Help You: Pension Knowledge and Retirement Decision-making. *The Review of Economics and Statistics*, 90 (2): 253–266.

Cheema, Amar and Dilip Soman. 2006. Malleable Mental Accounting: The Effect of Flexibility on the Justification of Attractive Spending and Consumption Decisions. *Journal of Consumer Psychology*, 16 (1): 33–44.

Collins, Debbie. 2003. Pretesting Survey Instruments: An Overview of Cognitive Methods. *Quality of Life Research*, 12 (3): 229–238.

Collins, J. Michael. 2007. Exploring the Design of Financial Counseling for Mortgage Borrowers in Default. *Journal of Family and Economic Issues*, 28 (2): 207–225.

Collins, J. Michael and Collin M. O'Rourke. 2010. Financial Education and Counseling—Still Holding Promise. *Journal of Consumer Affairs*, 44 (3): 483–498.

Collins, J. Michael and Maximilian D. Schmeiser. 2013. The Effects of Foreclosure Counseling for Distressed Homeowners. *Journal of Policy Analysis and Management*, 32 (1): 83–106.

Collins, J. Michael, Eric S. Belsky, and Karl E. Case. 2005. Exploring the Welfare Effects of Risk-based Pricing in the Subprime Mortgage Market. In *Building Assets, Building Credit: Creating Wealth in Low-income Communities*, edited by Nicolas P. Retsinas and Eric S. Belsky (132–151). Washington, DC: Brookings Institution Press.

Collins, J. Michael, Christi Baker, and Rochelle Gorey. 2007. Financial Coaching: A New Approach for Asset Building. A report for the Annie E. Casey Foundation. PolicyLab Consulting Group, LLC.

Courchane, Marsha, Adam Gailey, and Peter Zorn. 2008. Consumer Credit Literacy: What Price Perception? *Journal of Economics and Business*, 60 (1–2): 125–138.

Dietz, Robert D. and Donald R. Haurin. 2003. The Social and Private Micro-level Consequences of Homeownership. *Journal of Urban Economics*, 54: 401–450.

Ding, Lei, Roberto Quercia, and Janneke Ratcliff. 2008. Post-purchase Counseling and Default Resolutions among Low- and Moderate-income Borrowers. *Journal of Real Estate Research*, 30 (3): 315–344.

Elliehausen, Gregory and Edward C. Lawrence. 2001. *Payday Advance Credit in America: An Analysis of Customer Demand, Monograph #35*. Washington, DC: Credit Research Center, McDonough School of Business, Georgetown University.

Foote, Christopher L., Kristopher S. Gerardi, and Paul S. Willen. 2012. Why Did So Many People Make So Many Ex Post Bad Decisions? The Causes of the Foreclosure Crisis, Working Paper Series 2012-7. Atlanta, GA: Federal Reserve Bank of Atlanta.

Gigerenzer, Gerd. 1991. How to Make Cognitive Illusions Disappear: Beyond "Heuristics and Biases". *European Review of Social Psychology*, 2 (1): 83–115.

Grant, Anthony M. 2008. Past, Present and Future: The Evolution of Professional Coaching and Coaching Psychology. In *Handbook of Coaching Psychology: A Guide for Practitioners*, edited by Stephen Palmer and Alison Whybrow. London: Routledge.

Green, Richard K. and Michelle J. White. 1997. Measuring the Benefits of Homeowning: Effects on Children. *Journal of Urban Economics*, 41 (May): 441–461.

Hayes, Eileen and Karen A. Kalmakis. 2007. From the Sidelines: Coaching as a Nurse Practitioner Strategy for Improving Health Outcomes. *Journal of the American Academy of Nurse Practitioners*, 19 (11): 555–562.

Heath, Chip and Jack B. Soll. 1996. Mental Budgeting and Consumer Decisions. *Journal of Consumer Research*, 23 (June): 40–52.

Hirad, Abdighani and Peter Zorn. 2002. A Little Knowledge Is a Good Thing: Empirical Evidence of the Effectiveness of Pre-purchase Homeownership Counseling. In *Low-income Homeownership: Examining the Unexamined Goal*, edited by Nicolas P. Retsinas and Eric S. Belsky (146–174). Cambridge, MA: Joint Center for Housing Studies of Harvard University.

Hung, Angela A. and Joanne K. Yoong. 2010. Asking for Help: Survey and Experimental Evidence on Financial Advice and Behavior Change. RAND Labor and Population Working Paper Series WR-714-1. Washington, DC: RAND.

Johnson, Kathleen W. and Geng Li. 2011. Are Adjustable-Rate Mortgage Borrowers Borrowing Constrained? FEDS Working Paper 2011-21. Washington, DC: Federal Reserve Board.

Johnson, Eric J., Stephen A. Atlas, and John W. Payne. 2011. Time Preferences, Mortgage Choice, and Strategic Default, Working Paper. New York: Columbia Business School.

Kahneman, Daniel and Amos Tversky. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47 (2): 263–291.

Karlan, Dean and Jonathan Zinman. 2008. Lying about Borrowing. *Journal of the European Economic Association*, 6 (2–3): 510–521.

Lax, Howard, Michael Manti, Paul Raca, and Peter Zorn. 2004. Subprime Lending: An Investigation of Economic Efficiency. *Housing Policy Debate*, 15: 533–572.

Levinger, Benjamin, Marques Benton, and Stephan Meier. 2011. The Cost of Not Knowing the Score: Self-estimated Credit Scores and Financial Outcomes. *Journal of Family and Economic Issues*, 32 (4): 566–585.

Louie, Josephine, Eric S. Belsky, and Nancy McArdle. 1998. *The Housing Needs of Low-Income Homeowners, Joint Center for Housing Studies W98–8*. Cambridge, MA: Harvard University.

Lusardi, Annamaria and Peter Tufano. 2009. Debt Literacy, Financial Experiences and Overindebtedness, Working Paper 14808. Cambridge, MA: National Bureau of Economic Research.

McCarthy, George W. and Roberto G. Quercia. 2000. Bridging the Gap between Supply and Demand: The Evolution of the Homeownership, Education, and Counseling Industry, Institute Report No. 00-01. Washington, DC: The Research Institute for Housing America.

Meier, Stephan and Charles Sprenger. 2007. Selection into Financial Literacy Programs: Evidence from a Field Study. Federal Reserve Bank of Boston Discussion Paper (07–5 (November)).

Meier, Stephan and Charles Sprenger. 2010. Present-biased Preferences and Credit Card Borrowing. *American Economic Journal: Applied Economics*, 2 (1): 193–210.

Meier, Stephan and Charles Sprenger. In press. Discounting Financial Literacy: Time Preferences and Participation in Financial Education Programs. *Journal of Economic Behavior and Organization*.

Molloy, Raven and Hui Shan. 2011. The Post-Foreclosure Experience of U.S. Households, Finance and Economics Discussion Series 2011-32. Washington, DC: Federal Reserve Board, Divisions of Research & Statistics and Monetary Affairs.

Moulton, Stephanie. 2012. Homebuyer Education and Mortgage Outcomes. In *Financial Decisions Across the Life Span: Problems, Programs and Prospects*, edited by Douglas Lamdin. New York: Springer.

Navarro-Martinez, Daniel, Linda Court Salisbury, Katherine N. Lemon, Neil Stewart, William J. Matthews, and Adam J.L. Harris. 2011. Minimum Required Payment and Supplemental Information Disclosure Effects on Consumer Debt Repayment Decisions. *Journal of Marketing Research*, 68 (Special Issue 2011): S60–S77.

Perry, Vanessa Gail. 2008. Is Ignorance Bliss? Consumer Accuracy in Judgments about Credit Ratings. *Journal of Consumer Affairs*, 42 (2): 189–205.

Quercia, Roberto and Lei Ding. 2009. Loan Modifications and Redefault Risk: An Examination of Short-term Impacts. *Cityscape: A Journal of Policy Development and Research*, 11 (3): 171–193.

Quercia, Roberto G., George W. McCarthy, and Susan M. Wachter. 2003. The Impacts of Affordable Lending Efforts on Homeownership Rates. *Journal of Housing Economics*, 12 (1): 29–59.

Rademacher, Ida, Kasey Wiedrich, Signe-Mary McKernan, and Megan Gallagher. 2010. *Weathering the Storm: Have IDAs Helped Low-Income Homebuyers Avoid Foreclosure?* Washington, DC: Center for Economic Development.

Reid, Caroline K. 2006. Locating the American Dream: Where Do Low-income Home Owners Live?. In *Chasing the American Dream: Multidisciplinary Perspectives on Affordable Homeownership*, edited by William M. Rohe and Harry Watson. Ithaca, NY: Cornell University Press.

Rooij, Maarten van, Annamaria Lusardi, and Rob Alessie. 2011. Financial Literacy, Retirement Planning, and Household Wealth. Working Papers No. 2011/21. Center for Financial Studies: Goethe-Universität, Frankfurt am Main, Germany.

Servon, Lisa J. and Robert Kaestner. 2008. Consumer Financial Literacy and the Impact of Online Banking on the Financial Behavior of Lower-income Bank Customers. *Journal of Consumer Affairs*, 42 (Summer): 271–305.

Shah, Anuj K., Sendhil Mullainathan, and Eldar Shafir. 2012. Some Consequences of Having Too Little. *Science*, 338 (November): 682–685.

Soll, Jack B., Ralph L. Keeney, and Richard P. Larrick. 2013. Consumer Misunderstanding of Credit Card Use, Payments, and Debt: Causes and Solutions. *Journal of Public Policy & Marketing*, 32 (1): 66–81.

Stewart, Neil. 2009. The Cost of Anchoring on Credit-card Minimum Repayments. *Psychological Science*, 20 (1): 39–41.

Thaler, Richard H. 1981. Some Empirical Evidence on Dynamic Inconsistency. *Economic Letters*, 8: 201–207.

Tidwell, Lynette, Stephen K. Holland, Jay Greenberg, Joelyn Malone, Joseph Mullan, and Robert Newcomer. 2004. Community-based Nurse Health Coaching and Its Effect on Fitness Participation. *Lippincott's Case Management*, 9 (6): 267–279.

US Department of the Treasury. 2010. Financial Education Core Competencies; Comment Request. *Federal Register*, 75 (165): 52596.

Ülkümen, Gülden, Manoj Thomas, and Vicki G. Morwitz. 2008. Will I Spend More in 12 Months or a Year? The Effect of Ease of Estimation and Confidence on Budget Estimates. *Journal of Consumer Research*, 35 (August): 245–256.

Van Zandt, Shannon and William M. Rohe. 2006. Do First-time Home Buyers Improve Their Neighborhood Quality? *Journal of Urban Affairs*, 28 (5): 491–510.

Van Zandt, Shannon and William M. Rohe. 2011. The Sustainability of Low-income Homeownership: The Incidence of Unexpected Costs and Needed Repairs among Low-income Home Buyers. *Housing Policy Debate*, 21 (2): 317–341.

Zinman, Jonathan. 2009. Where Is the Missing Credit Card Debt? Clues and Implications. *Review of Income and Wealth*, 55 (2): 249–265.