

# PORTFOLIO ADJUSTMENT TO HOME EQUITY ACCUMULATION AMONG CRA BORROWERS

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**Portfolio Adjustment to Home Equity Accumulation  
among CRA Borrowers**

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**Abstract**

*This paper identifies the financial implications of equity accumulation for low- and moderate-income (LMI) borrowers. The analysis examines (1) whether the accumulation of equity crowds out other investments, and (2) whether equity is substantially extracted from net worth through other borrowing activities. The data come from a unique panel study of Community Reinvestment Act (CRA) borrowers and matched renters. A copula modeling approach estimates the distribution of a financial portfolio; the distribution is used to simulate the hypothetical effect of equity accumulation on the portfolios of the matched renters. The analysis reveals no evidence that equity accumulation crowds out other investment activities, nor do we find excessive borrowing against equity by CRA beneficiaries.*

## **1. Introduction**

Homeownership is assumed to build wealth in two ways: it forces owners to save by paying down the principal owed and it increases owners' net worth when the house appreciates beyond the cost of the down payment and mortgage. For many Americans, especially less affluent Americans, the resulting home equity represents the greater part of their household wealth. This is especially true for lower income people: the Joint Center for Housing Studies estimates that home equity makes up almost 80 percent of the wealth of the median owner with income below \$20,000 (Di 2003).

In 1977, Congress passed the Community Reinvestment Act (CRA). The Act placed upon banks the affirmative obligation that they meet the credit needs of the communities in which they are chartered, consistent with the "safe and sound operation" of the issuing institutions. Regulated financial institutions can meet their CRA obligations in a variety of ways, one of which is through the provision of affordable home loans. While not limited to the promotion of mortgage finance, CRA has served to extend the financial benefits of homeownership to low- and moderate-income people.

There has been much debate among scholars regarding the financial implications of facilitating homeownership for low- and moderate-income households through the CRA (Russakoff 2008, Seidman 2009, Silver and Marsico 2009). Homeownership has long been understood as a mechanism for consistently adding value to net worth through the accumulation of equity (Hollaway 1991, Turner 2009). Yet, especially in the context of the contemporary real estate market, many question the wisdom of encouraging ownership when renting often appears a lower-risk and more affordable option

(Fratantoni 1998, Smith and Smith 2007). Though much research has considered the performance of home equity as an investment instrument in general (Walden 1983, Hansen and Skak 2008), surprisingly few studies have focused specifically on the role of equity accumulation in the portfolios of low- and moderate-income borrowers. Our research fills this gap.

In this study we seek to understand how lower-income borrowers' portfolios respond to the accumulation of home equity associated with their CRA loans. Two potential negative consequences of the use of home equity as an investment mechanism are, first, the crowding out of other investment tools and a resulting under-diversification of the portfolio (Turner 2003, Hilber 2005) and, second, the tendency to over-borrow against equity (Klyuev and Mills 2007, Benjamin and Chniloy 2008).

In response to these concerns, we direct our investigation towards two important questions: first, are CRA homeowners increasing their levels of borrowing in response to the accumulation of home equity; and second, are CRA borrowers limiting their investments in other financial instruments and savings, effectively establishing the accumulation of home equity as a substitute for other wealth-building activities. We answer these questions using data from a unique panel study, the Community Advantage Program (CAP) study, which links extensive loan-level information with in-depth household-level survey data. All homeowners in the CAP study received affordable, fixed-rate, CRA mortgages, so the CAP data allow us to assess the financial implications of equity accumulation for CRA borrowers.

## **2. Equity Accumulation and CRA Borrowers**

Many scholars have noted the positive externalities of homeownership including better scholastic performance of children (Barker and Miller 2009), better maintenance of neighborhoods (Santiago et al. 2010), greater neighborhood stability (Rohe, McCarthy, and Van Zandt 2000), and a higher level of voluntary and civic engagement (ibid). However, the driving argument in support of promoting homeownership to low- and moderate-income people has been that owning a home provides financial benefits, principally the accumulation of equity.

The question naturally arises as to whether the accumulation of equity offsets the additional costs of homeownership relative to renting, i.e. home maintenance (Evans 1995), lower mobility (Gabriel and Painter 2008), and risk in the real estate market (Saegert, Fields and Libman 2009). Even if the accumulation of equity outweighs the true costs of homeownership, some have argued that that the purchase of a home is inadvisable for investment reasons. Two of the major criticisms of the pursuit of equity are that it crowds out other investment options and that it is diminished through excessive borrowing. We examine here the literature on these critiques.

How might the home serve to crowd out other investment options? First, the scale of investment in the home is fairly inflexible, meaning the consumer cannot adapt the amount allocated to the mortgage payment to the expected return on investment in the home. Though there may be some leeway available in terms of the down payment amount, building equity requires a regular and fairly invariant payment. Especially for LMI borrowers, due to their well-documented comparatively high marginal propensity to

consume (Fan 2006), the mortgage payment may represent a large proportion of income, leaving little for other investments and resulting in an under-diversified portfolio.

Second, the home is by nature illiquid and its exchange generally involves significant costs (McCarthy, Van Zandt, and Rohe 2001); one cannot buy and sell the housing investment rapidly and inexpensively as one might trade other investment instruments in order to maximize returns.

A second criticism of the home as an investment instrument is that the associated wealth gains are diminished through excessive borrowing. While the accrual of equity might be a benefit for low- and moderate- income households, it comes with the temptation to borrow that money back for other uses. It is true of any asset that an investor must be careful regarding decisions to leverage that asset in the form of new borrowing, but in the case of home equity, this is particularly important since there is an entire industry devoted to soliciting homeowners to borrow against their home. The subprime mortgage market arose in the 1980s to extend cash-out refinance and debt consolidation loans to borrowers with weak credit but plenty of home equity. In 1986, when tax reform meant taxpayers could no longer deduct consumer loan interest but could still deduct home mortgage interest, homeowners began shifting debt to their homes by borrowing against them to fund purchases and pay off consumer debt.

A critical task in evaluating the financial impact of CRA lending is to determine whether LMI borrowers (1) accumulate too much debt along with their equity or (2) would be well invested and diversified in other instruments in lieu of the investment in the home. It is important to note that with regards to the second issue, we are not trying

to render a comprehensive theoretical assessment of the *potential* alternative investments to homeownership, as is done by Cauley, Pavlov and Schwartz (2007), but are instead attempting to determine whether there is evidence that the accumulation of equity crowds out other investing activity.

In the next section we examine the financial effects of equity accumulation among CRA borrowers in detail.

### **3. Empirical Analysis**

The data we use come from a six-year-long panel study conducted as part of the Community Advantage Program. CAP began as a secondary mortgage market program developed out of a partnership between the Ford Foundation, Fannie Mae, and Self-Help, a leading community development financial institution. Under the CAP program, participating lenders are able to sell nonconforming CRA mortgages to Self-Help, which then securitizes and sells them to Fannie Mae and other investors; Self-Help retains recourse on these loans. CAP loans are characterized by flexible underwriting that usually requires little or no down payment, high debt burdens, nontraditional proofs of creditworthiness, and sometimes no requirement for mortgage insurance. CAP borrowers are either low-income, LMI minority borrowers, or LMI borrowers in low-income or minority neighborhoods. By the end of 2004, more than 28,000 families had purchased homes through lenders participating in the CAP programs.

Who are CAP's borrowers? CAP's borrowers are concentrated in the southeastern United States and tend to live in more developed regions, with only 12 percent living in rural areas. The median borrower is 32 years old. Some 41 percent of

CAP's borrower households are headed by a woman and almost half of CAP borrowers have children living in the home. Approximately 57 percent of CAP borrowers are white, 58 percent are married or in a committed relationship, and 88 percent have at least a high school diploma. CAP's borrowers have a median annual household income of \$30,972 (an amount that represents 59 percent of area median income). The median loan balance at origination for CAP's borrowers was \$80,985, and this amount was issued at an interest rate of 7.13 percent.

In 2004, the Center for Community Capital at the University of North Carolina, Chapel Hill began conducting annual surveys with a panel of CAP participants to evaluate the impacts of homeownership on their lives. In order to conduct this analysis, a random sample of CAP borrowers was selected to participate in a series of annual surveys. Once the sample of homeowners was selected, a comparison group of renters was matched to the homeowners based on neighborhood proximity and income. This matching was limited to the 30 metropolitan areas in the United States with the highest number of CAP owners. The renter sample was obtained by randomly selecting households who lived within the same census blocks as participating homeowners, based on public telephone directory lists. Like the CAP homeowners, the renters had to have an annual income no more than 80 percent of area median income (AMI) if white or no more than 115 percent of AMI if non-white. Respondents also had to be between 18 and 65 years old and pay rent to the owner of their residence.

This current study draws on two years of CAP data and focuses on 982 owners and 595 renters matched to owners. (See Table 1 for a descriptive overview of owners

and renters.) The two years in question, 2005 and 2008, are the years in which the panel survey included an extensive module related to participants' finances and wealth holdings. The goal in this current study is to identify any possible effect of equity accumulation on the rest of the respondents' financial portfolios.

In our method, we intend to describe respondents' financial portfolios as a system where the individual components are dependent upon each other. As we will show below, the data from our survey are very non-normal, with high kurtosis. The data are therefore unfit for methods designed for normally distributed data, such as seemingly unrelated regression. Multivariate copulas have seen broad application in economic applications lately (see e.g. Chan and Kroese 2010; Eluru et al. 2010; Zhao and Zhou 2010), and their development is motivated, at least in part, to handle dependence (i.e. correlation) among non-normal variables (Papaefthymiou and Kurowicka 2009). In this approach to multivariate modeling, flexible univariate distributions are used to describe the individual variables (margins), and dependence structures are introduced to the model via a copula function. The marginal and copula parameters give the full joint distribution of the variables under study (Sungur 2000). From this joint distribution, all quantities of interest – conditional distributions/expectations (i.e. regression functions), bivariate distributions, variances and conditional variances – can be derived. What is of greatest interest to us is that, using the joint distribution derived from the copula, we can derive the adjustment of any element of the financial portfolio in response to a shift in home equity.

Similar to the approach in Cutter and DeWoody (2010), we use simulation to explore the results from our empirical analysis. In the first step we estimate the copula

and marginal parameters on demographic and financial characteristics of CRA owners (specifically, those CAP owners who remained owners through the end of the study in 2008). Next, for the renters (again, who remained renters through the end of the study in 2008) matched to these owners, we give them the home equity of their matches, and draw 10,000 times a set of *response* variables. These *response* variables are dependent upon a set of *fixed* variables that we draw from the literature as likely to be determinants of the *response* variables, but not dependent upon home equity values. We identify the effect of equity accumulation to be the simulated change in the renters' *response* variables, that is, the difference in their simulated portfolio values accounting for the matched owners' home equity and the observed values of the renters' response variables. We feel that this design comes close to answering the question a policymaker should pose in evaluating CRA: what, if anything, would be the effect of placing an eligible renter in the condition of CRA-funded homeownership? The particular copula functions that we use result in somewhat nonlinear relationships between home equity and the rest of the portfolio, so we choose to present our results graphically in the main text and report the marginal and copula parameter estimates in Appendix 1.

In selecting the *response* and *fixed* variables, we turn to the literature to identify factors that may be influenced by home equity, and choose the *fixed* (i.e. control) variables that correspond to those which have been identified to influence one or more of

our *response* variables. We consider the relationships between home equity and the assets constituting the following variables – all measured in 2008 dollars.<sup>1</sup>

#### Response Variables

1. Transactions account balances (total amount held in all checking, savings, and CDs at the time of the interview)
2. Investments (stocks, bonds, mutual funds, retirement accounts)
3. Credit/charge card debt
4. Equity (value - corresponding debt<sup>2</sup>) in non-primary-residence properties and major durables (vacation homes, commercial property, land, investment properties, vehicles and timeshares)
5. Student loan debt
6. Borrowing against the home (value of home equity lines of credit + second mortgage value + cash-out refinance amount)

#### Fixed Variables

1. Age
2. Income
3. Education (a seven point ordinal scale: 1= No HS diploma, 2= High school graduate / GED, 3 = Some college/trade school but no degree, 4 = Associate degree/trade school certificate/ non-traditional: vocational or other license , 5 =

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<sup>1</sup> Since many financial institutions consider the loan-to-value ratio rather than the raw value of home equity in making lending decisions (i.e. home equity lines of credit), we run the model with just home equity, just LTV, and home equity as well as LTV.

<sup>2</sup> For equity in non-primary-residence properties and major durables, both value and debt levels were reported by respondents.

- Bachelors degree, 6 = Some graduate school but no graduate degree, 7 = Graduate or professional degree)
4. Number of children
  5. Race (black, Hispanic, or non-Hispanic white/other)
  6. Home equity (home value<sup>3</sup> - mortgage balance at interview time)

We repeat the model for both cross-sectional amounts in 2008 and change from 2005 to 2008. It is important to note that the questions about debt related to non-housing equity (*response* variable number four) were not asked in the 2005 wave of the survey. We use multiple imputation to deal with these missing variables. Appendix 2 gives the details of our imputation exercise.

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<sup>3</sup> This paper calculates home values using a zip code-level house price index that is proprietary to Fannie Mae. The Fannie Mae index provides a more accurate estimate of home value than do publicly available house price indices (such as the FHFA index, formerly OFHEO) because it relies on information at the zip code, rather than MSA or state, level.

	<b>Owners</b>				<b>Renters</b>			
	<i>Levels in 2008</i>				<i>Levels in 2008</i>			
	Mean	Std. Dev	Skew	Kurtosis	Mean	Std. Dev	Skew	Kurtosis
Home Equity \$ Transactions	28770.11	32949.37	2.06	11.5304	–	–	–	–
Accounts \$	6305.41	14816.4	7.48	90.2671	3642.369	13071.408	15.4	353.585
Investments \$ Non-Residence	7199.326	32485.9	13.51	269.506	5804.198	47879.916	20.76	508.711
Equity \$	17148.77	77764.18	13.6	256.938	11374.36	112101.57	25.47	728.198
Credit Card								
Debt \$	4362.222	6801.78	2.406	10.0687	2271.514	5581.6178	4.417	28.7727
Student Loan								
Debt \$	5836.767	14830.54	3.708	19.4484	6082.269	16912.427	4.157	23.1569
Borrow Against								
Home \$	3056.626	10905.23	5.311	39.6836	–	–	–	–
Age (yrs)	37.14769	10.7956	0.991	3.78591	40.0654	12.824345	0.465	2.25792
Income \$	51580.06	31779.59	1.679	7.83731	42572.93	32107.788	1.68	7.51288
Number of								
Children	1.165128	1.222821	1.024	4.13315	0.94702	1.1715381	1.26	4.3269
% With								
Bachelor's Deg.	30	–	–	–	25	–	–	–
% Black	20	–	–	–	37	–	–	–
% Hispanic	16	–	–	–	29	–	–	–
	<i>Change from 2005-2008</i>				<i>Change from 2005-2008</i>			
Home Equity \$ Transactions	-1732.86	48797.06	-7.86	126.399	–	–	–	–
Accounts	2782.387	13313.68	8.661	124.478	1309.88	11501.425	15.3	374.145
Investments \$ Non-Residence	4712.75	30195.08	14.09	294.957	3939.237	46268.721	20.48	498.073
Equity \$	10451.71	95714.81	6.307	106.187	8633.214	115970.79	22.76	622.31
Credit Card								
Debt \$	977.1364	6850.144	0.703	12.6765	548.2614	5375.2752	2.559	29.1222
Student Loan								
Debt \$	1648.174	9949.249	2.679	21.6149	2302.552	12388.364	4.557	40.6862
Number of								
Children	0.14359	0.866853	0.533	7.97039	0.09851	0.8602794	0.349	12.0859
Borrow Against								
Home \$	-205.003	13733.96	-0.11	26.8647	–	–	–	–
Income \$	15194.55	28091.67	1.921	10.515	12824.29	26634.285	1.899	10.1916
% With								
Bachelor's Deg.	3	–	–	–	4	–	–	–

Note: Summary statistics given for the sample composed of the 982 owners and 595 renters. All financial variables are given in 2008 dollars.

**Table 1: Descriptive Statistics**

A critical choice in the modeling process is the specification of the marginal distributions. As can be seen by the empirical kurtosis in the fourth column of Table 1, the tails in the data are very heavy (the kurtosis of a normally distributed random variable is 3 (Boutahar 2010)). There are four types of variables in our data, a dichotomous variable, race, which we break down into three binary variables (black, Hispanic, or non-Hispanic white/other); a bounded discrete variable, education, which is a seven-point ordinal variable; strictly non-negative variables, such as credit card debt, second mortgage value, investments, etc.; unbounded variables, such as net-worth and 2005-2008 changes in non-negative variables. We select marginal distributions that can accommodate the support of the variables we are working with and also allow for heavier than normal tails. For race we use a Bernoulli distribution, for education we use a beta-binomial distribution, which allows for variance beyond that of the binomial, the three-parameter zero-adjusted inverse-Gaussian distribution for the non-negative variables, and the three-parameter generalized Student's T distribution for the unbounded variables. See Rigby and Stasinopoulos (2005) for details on these distributions.

The next step in specifying our model is to choose the copula function. One challenge in the construction of our model is that we seek to estimate the dependence relations among a mixture of discrete (e.g. race) and continuous (e.g. equity) random variables. This means it is inappropriate to use many of the copulas developed for and/or applied to financial data in previous work because of their inability to accommodate discrete margins (Sungur 2000). We use the Bayesian estimator developed by Pitt, Chan and Kohn (2006) to estimate a multivariate normal dependence structure for a mixture of

discrete and continuous variables. This is very convenient in that we can accommodate the non-normal shapes and different support types of the margins, as well as using the very familiar multivariate normal correlation matrix to describe dependence.<sup>4</sup>

We present our results in a series of graphics below. In each figure there are two plots. The plot labeled “Level” refers to the results from the 2008 cross-sectional analysis, and the plot labeled “Change” refers to the 2005-2008 change model. In each “Level” analysis, the x-axis gives the amount of home equity transferred to the matched renter, and the y-axis gives the simulated change in the renter’s asset/debt. In the “Change” analysis, the x-axis gives the difference in 2008 and 2005 home equity that is transferred to the renter, and the y-axis gives the difference between the simulated 2005 to 2008 change in the debt or asset value and the actual change experienced by the matched renter. All quantities are in 2008 dollars. We use confidence intervals around the effects to determine whether it is likely that large negative reactions in portfolio components result from the accumulation of equity. The points are placed at actual home equity values from the sample, and 99 percent confidence intervals from the simulation are placed around the estimates. We use 99 percent confidence intervals in the interest of conservative inference. Since there is little reason to believe that equity accumulation will positively impact other investments or reduce debt, the finding that would favor CRA as a policy prescription would be that home equity accumulation has a relatively small effect on the other portfolio components. In order to consider any possible large effects of home equity, we draw larger than conventional confidence intervals, and bias our

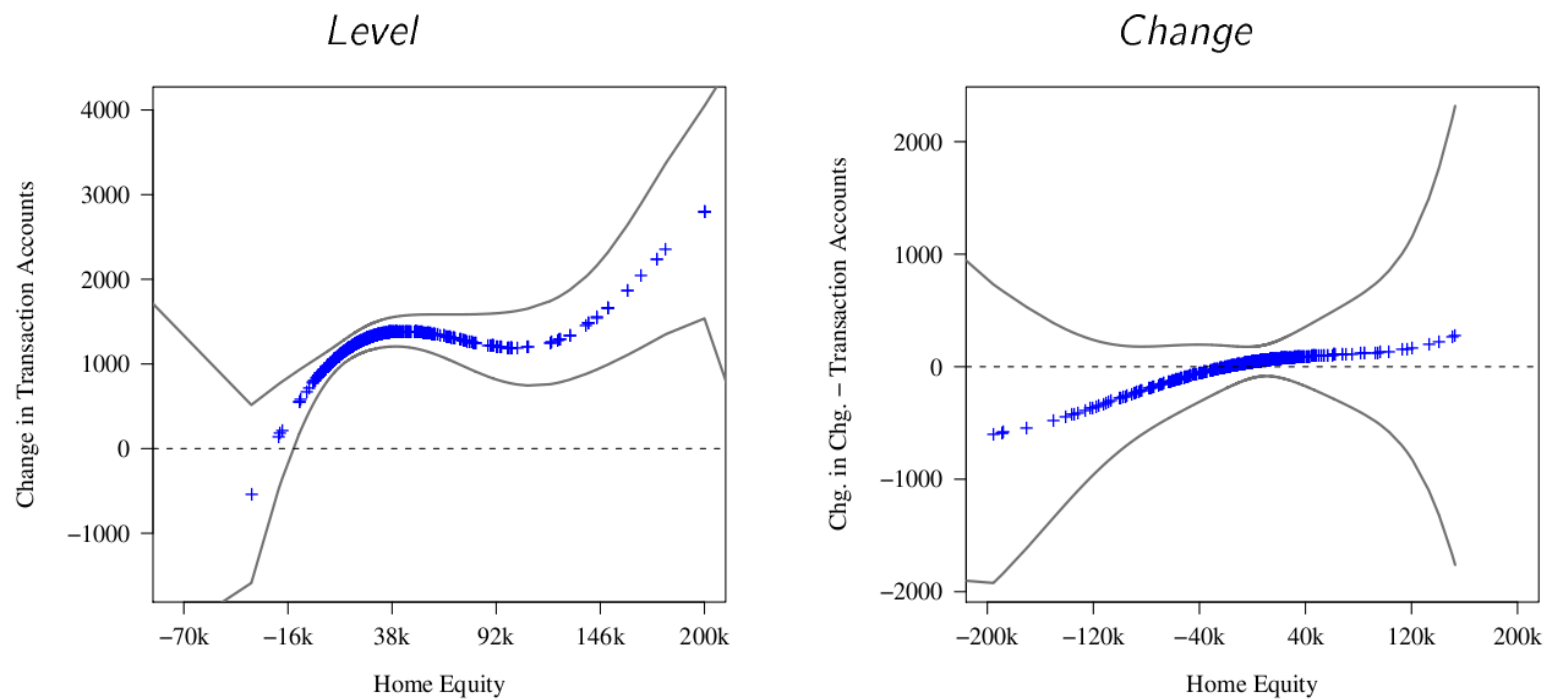
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<sup>4</sup> All analyses were conducted in the R statistical software. Replication code is available from the authors upon request.

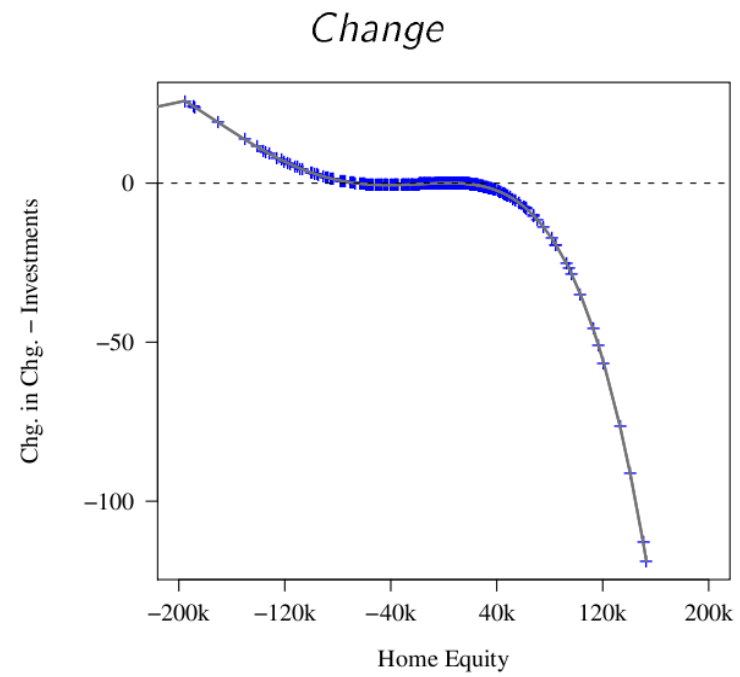
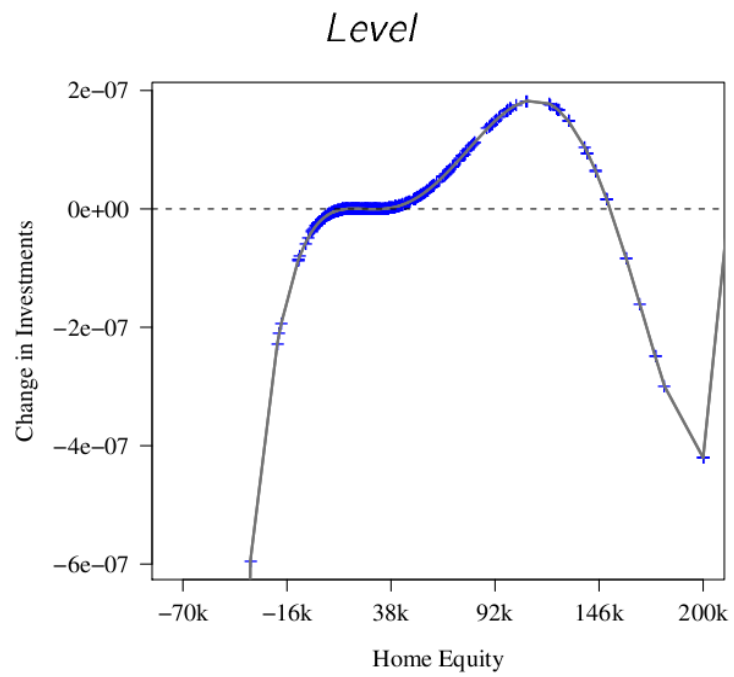
analysis toward concluding that large increases in debt or decreases in other assets are plausible outcomes. This way, if large (i.e. offsetting) effects lie outside of the confidence bands, we can feel justified in claiming that CRA loans represent a strong forced-savings mechanism for the target borrowers, in that equity accumulation does not result in offsetting negative reactions in the portfolio.<sup>5</sup>

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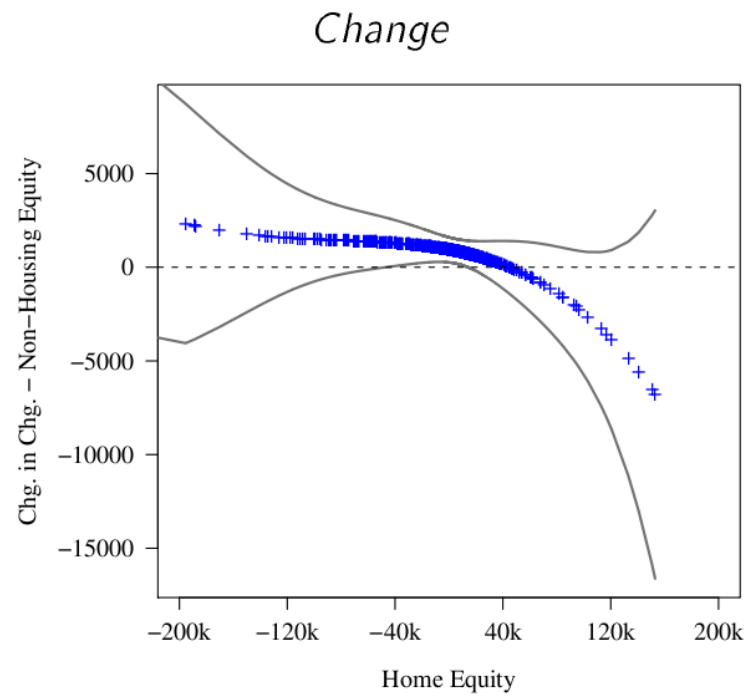
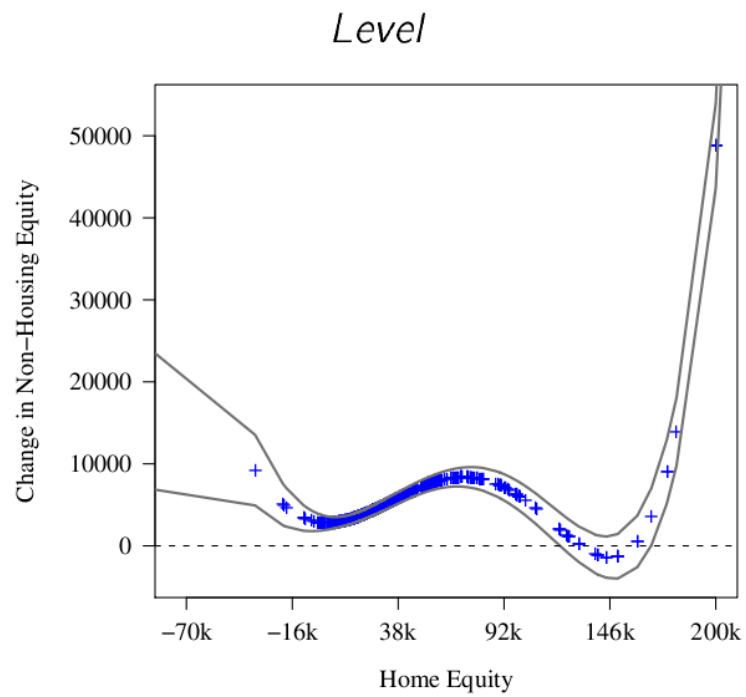
<sup>5</sup> All of the results reported use current house value - current loan value to determine home equity. Results using LTV did not differ substantively from the results using home equity.



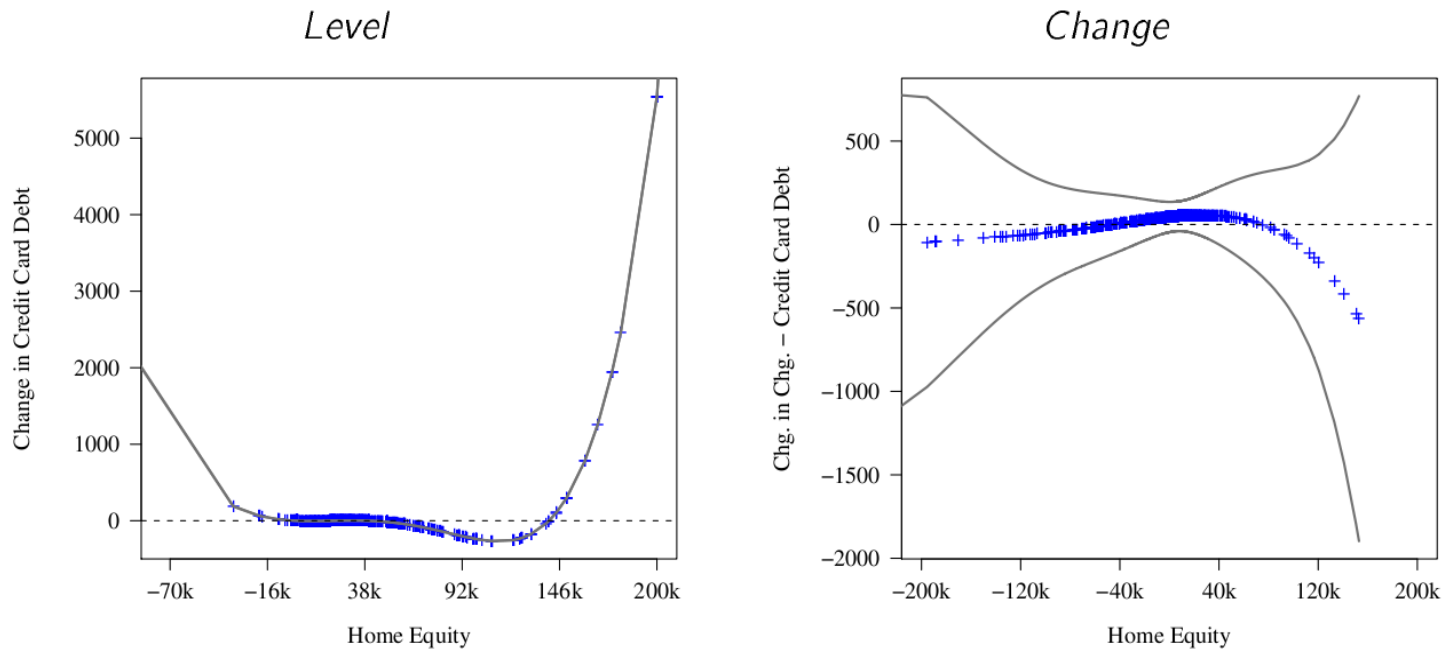
**Figure 1:** The relationship between Home Equity and Transaction Account Balances



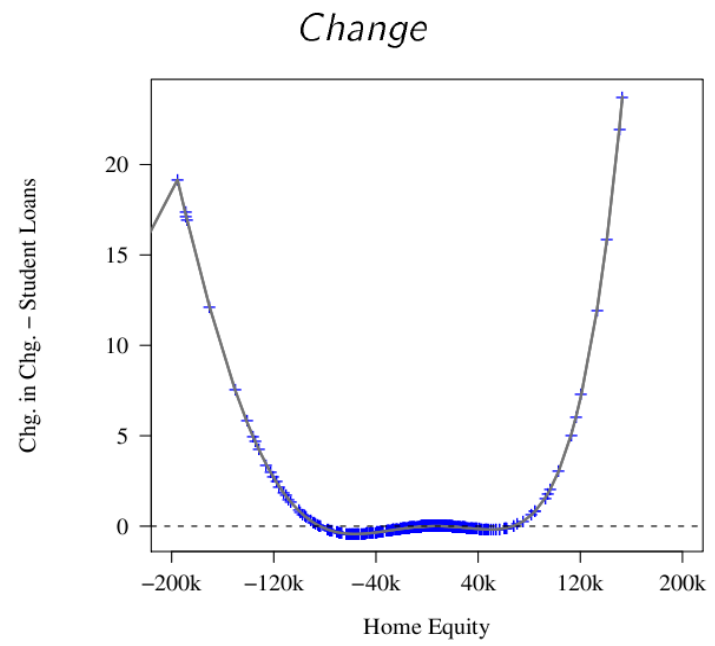
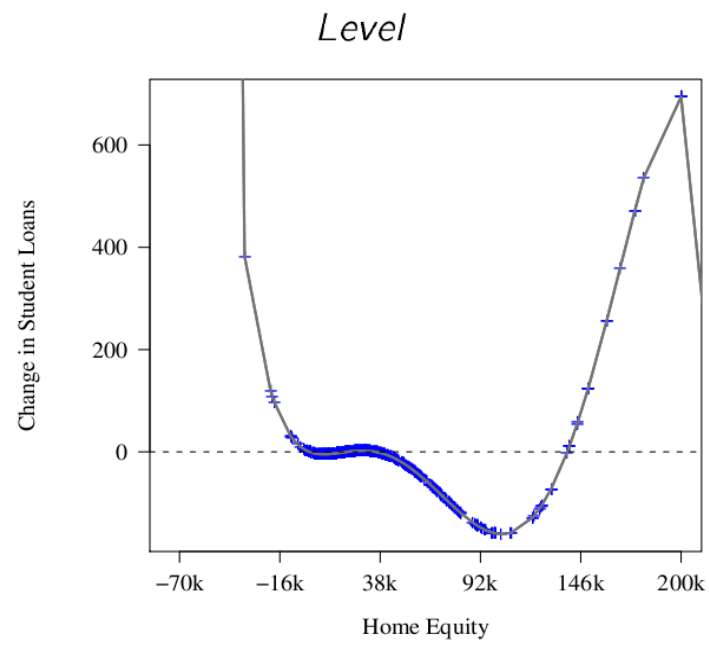
**Figure 2:** The relationship between Home Equity and the value of Investments



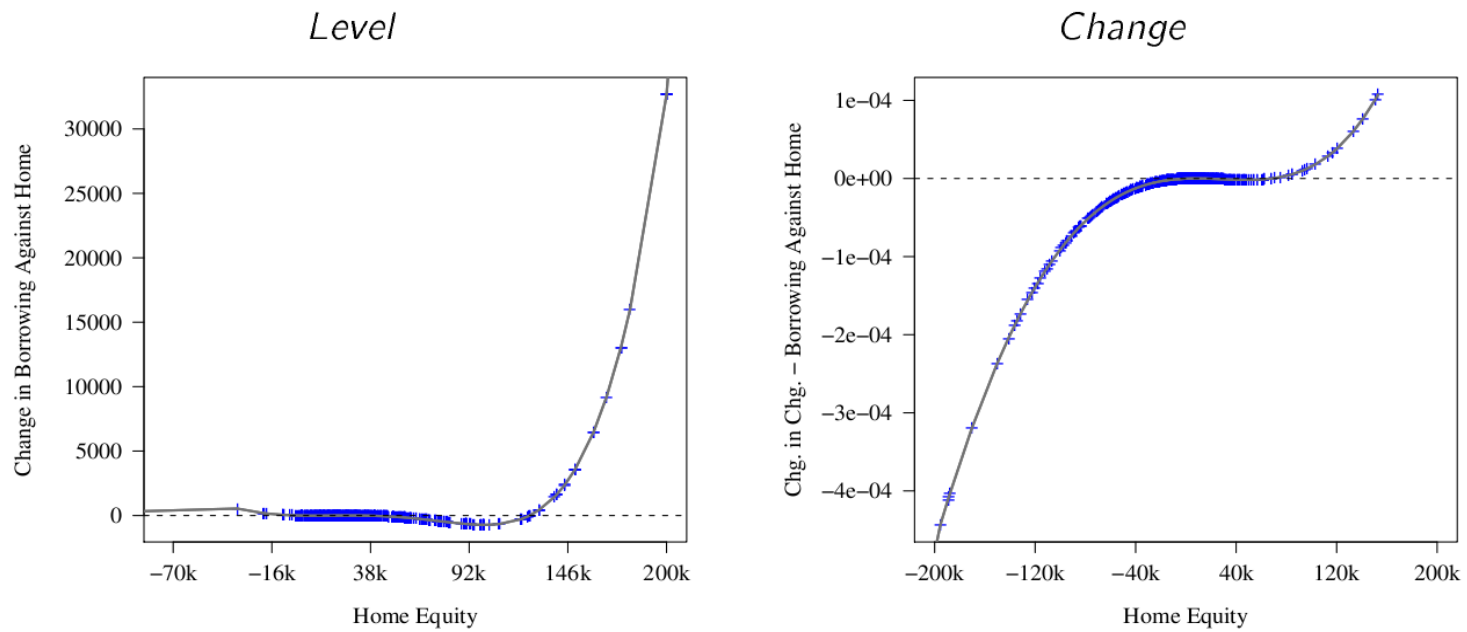
**Figure 3:** The relationship between Home Equity and Non-Primary Residence Equity



**Figure 4:** The relationship between Home Equity and Credit Card Debt



**Figure 5:** The relationship between Home Equity and Student Loan Debt



**Figure 6:** The relationship between Home Equity and Borrowing against the Home

The results from the empirical analysis provide strong support for the claim that CRA lending acts as a strong forced-savings tool. There is very little evidence that either alternative investments and/or savings are reduced as a result of equity accumulation or that debt is incurred at levels that offset equity-based gains in net worth. We now walk through the results regarding the individual asset/debt values.

First we consider the relationship between home equity and other assets. As the closed 99 percent confidence intervals indicate, the estimate of the relationship between home equity and investments is very precise. In the “Level” analysis, the effect is less than a penny for the entire observed range of home equity. In the change analysis, there does seem to be a negative relationship between change in home equity and change in investments, but this is a very small-scale relationship, with a \$120,000 increase in home equity corresponding to a \$100 reduction in investments. Non primary-residence equity does seem to exhibit a notable relationship with home equity: the majority of renters would be predicted to see an increase of approximately \$5,000 to \$10,000 given home equity between \$20,000 and \$90,000 in 2008. However, the “Change” analysis indicates that the accumulation of home equity over time is associated with a decline of approximately \$5,000 to \$15,000 in non-primary residence equity. Generally speaking, it appears there is not much reason to expect significant asset-related opportunity costs to home equity accumulation for CRA borrowers. We find little evidence that investments or savings suffer from the resources tied up in the generation of equity.

Now we consider debt accumulation, looking in particular for debt levels that might offset wealth gains from equity accumulation. We do see the possibility of a moderate positive relationship between the accumulation of home equity and credit card debt, particularly for those with higher levels of home equity: an accumulation of home equity greater than \$150,000 corresponds to an *average* predicted increase of \$1,000 or more in credit card debt. The scale of the relationship for the change analysis is much smaller, however, with the *maximum* upper-bound in the confidence interval of approximately \$700 increase in credit card debt as a result of home equity accumulation. Student loan debt, though precise, exhibits a very small-scale relationship with home equity accumulation: extremely high or low values of equity correspond with an increase of approximately \$600 in student loan debt. The change-in-time effect of home equity on student loan debt is negligible. The last relationship we consider is that between equity accumulation and borrowing against the home. As would be expected, the direction of the cross-sectional relationship is positive – people with more equity borrow against that equity – but the relationship is non-linear: notable borrowing against home equity only occurs at where equity levels are \$100,000 or greater, and such borrowing never reaches a scale that would offset wealth gains from home equity. The “Change” relationship is on a very small scale. This last result may seem counter-intuitive, since we might expect an increase in equity to correspond with an increase in borrowing against equity, but it may be that our compressed time scale of three years is simply not long enough to observe the expected equity-gain/borrowing cycle. Overall, we do find some evidence

that debt levels – credit card debt and borrowing against the home – may increase in response to substantial home equity accumulation, but there is no indication that these increases would come near the scale necessary to offset levels of home equity.

#### **4. Conclusion**

Many view the Community Reinvestment Act as a policy that clearly enhances opportunities for wealth-building among LMI families. However, some critics emphasize potential drawbacks of reliance upon homeownership as a wealth-building tool. Chief among the problems with homeownership are, first, that the scale of the investment is comparatively inflexible, and tends to tie up resources, which leads to under-diversification of the portfolio, and, second, that homeowners draw down the added value of home equity by borrowing against the home. Any policymaker must confront these potential drawbacks in the evaluation of CRA's true potential for wealth generation.

Few prior studies have focused directly on the financial implications of homeownership for CRA beneficiaries. We fill this gap. Using a unique panel study of CRA-financed homeowners and a matched sample of renters, we estimate the relationships between equity accumulation and major components of households' financial portfolios. Overall, though there appears to be some association between the accumulation of large amounts of equity – in the order of \$150,000 and greater – and an increased indebtedness of between 10 and 30 percent of that amount, this effect is far from expected for the typical LMI homeowner, and we find no evidence that debt accumulation offsets the wealth-building effect of home equity. Further, we find no

evidence of shortfalls in alternative investments or savings resulting from the growth of equity. In conclusion, it appears that CRA lending serves as an effective means for promoting stable wealth-building for LMI households through the forced-savings mechanism of equity accumulation.

## References

- Ardalan, K., Davis, A. 2006. Community reinvestment act and efficient markets debate: overview. *Journal of Economics and Economic Education Research*, 7, 3. p.53(18)
- Barker, D., & Miller, E. 2009. Homeownership and Child Welfare. *Real Estate Economics*, 37, 2. p.279(25)
- Beltrarto, K. and P. Bloom. 1987. Determining the Bandwidth of a Kernel Spectrum Estimate. *Journal of Time Series Analysis*, 8(1):21-38.
- Benjamin, J. D., & Chinloy, P. July 2008. Home Equity, Household Savings and Consumption. *The Journal of Real Estate Finance and Economics*, 37, 1. p.21(12)
- Boudt, K., Peterson, B., & Croux, C. 2008. Estimation and decomposition of downside risk for portfolios with non-normal returns. *Journal of Risk*, 11, 2. p.79(25)
- Boutahar, M. 2010. Behaviour of skewness, kurtosis and normality tests in long memory data. *Statistical Methods and Applications*, 19, 2. p.193(23)
- Cauley, S. D., Pavlov, A D, & Schwartz, E S. 2007. Homeownership as a Constraint on Asset Allocation. *The Journal of Real Estate Finance and Economics*, 34, 3. p.283(29)
- Chan, J. C., & Kroese, D. P. 2010. Efficient estimation of large portfolio loss probabilities in t-copula models. *European Journal of Operational Research*, 205, 2. p.361(7)

- Cutter, B. & DeWoody A. 2010. Parking Externalities in Commercial Real Estate. *Real Estate Economics*. 38(2). p.197
- DeMong, R. F., & Lindgren, J. H. 1999. How lenders are marketing home equity products. *Journal of Retail Banking Services*, 21, 1. p.31
- Di, Zhu Xiao. 2003. *Housing Wealth and Household Net Wealth in the United States: A New Profile Based on the Recently Released 2001 SCF Data*. Cambridge, MA: Joint Center for Housing Studies.
- Eluru, N., Bhat, C. R., Pendyala, R. M., & Konduri, K. C.2010. A joint flexible econometric model system of household residential location and vehicle fleet composition/usage choices. *Transportation*, 37, 4. p.603(24)
- Evans, M. 1995. Making affordable housing work. *Journal of Property Management*, 60, n2. p.50(4)
- Fan, C. S. 2006. Do the rich save more? A new view based on intergenerational transfers. *Southern Economic Journal*, 73, 2. p.362(12)
- Fratantoni, M. C. (July 1998). Homeownership and investment in risky assets. *Journal of Urban Economics*, 44, n1. p.27(16)
- Gabriel, S. A., & Painter, G. 2008. Mobility, Residential Location and the American Dream: The Intrametropolitan Geography of Minority Homeownership. *Real Estate Economics*, 36, 3. p.499(33)
- Hansen, J. D., & Skak, M. 2008. Adaptation investments and homeownership. *Journal of Housing Economics*, 17, 1. p.102(14)

- Hilber, C. A. 2005. Neighborhood externality risk and the homeownership status of properties. *Journal of Urban Economics*, 57, 2. p.213(29)
- Holloway, T. M. (April 1991). The role of homeownership and home price appreciation in the accumulation and distribution of household sector wealth. *BusinessEconomics*, 26, n2. p.38(7)
- Hurvich, C. M. 1985. Data-Driven Choice of a Spectrum Estimate: Extending the Applicability of Cross-Validation Methods. *Journal of the American Statistical Association*, 80(392):933-940.
- Imai, K., G. King and O. Lau. 2009. Zelig: Everyone's Statistical Software. R package version 3.4-5. URL: <http://CRAN.R-project.org/package=Zelig>
- King, G. 1989. Variance Specification in Event Count Models: From Restrictive Assumptions to a Generalized Estimator. *American Journal of Political Science*, 33(3):762-784.
- King, G., J. Honaker, A. Joseph and K. Scheve. 2001. Analyzing Incomplete Political Science Data: An Alternative Algorithm for Multiple Imputation. *The American Political Science Review*, 95(1):49-69.
- Klyuev, V., & Mills, P. 2007. Is housing wealth an 'ATM'? The relationship between household wealth, home equity withdrawal, and saving rates. *IMF Staff Papers*, 54, 3. p.539(23)

- McCarthy, G., S. Van Zandt, and W. Rohe. 2001. *The Economic Benefits and Costs of Homeownership*. Research Institute for Housing America Working Paper No. 01-02.
- Pitt, M., D. Chan, and R. Kohn. 2006. Efficient Bayesian inference for Gaussian Copula Regression Models. *Biometrika*, 93(3): 537 - 554.
- Papaefthymiou, G., & Kurowicka, D. Feb 2009. Using copulas for modeling stochastic dependence in power system uncertainty analysis. *IEEE Transactions on Power Systems*, 24, 1. p.40(10)
- R Development Core Team. 2009. R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing. ISBN 3-900051-07-0. URL: <http://www.R-project.org>
- Rigby R. A. & Stasinopoulos D. M. 2005. Generalized Additive models for location, scale and shape. *Journal of the Royal Statistical Society Series C*. 54(3), p. 507
- Rohe, W., G. McCarthy, and S. Van Zandt. 2000. *The Social Benefits and Costs of Homeownership*. Research Institute for Housing America Working Paper No. 00-01.
- Rubin, D. B. 1987. *Multiple Imputation for Nonresponse in Surveys*. New York: Wiley & Sons.
- Russakoff, A. 2008. Problems with the application of a metric for CRA compliance in banking. *Review of Business*, 29, 1. p.32(7).

- Saegert, S., Fields, D., & Libman, K. 2009. Deflating the Dream: Radical Risk and the Neoliberalization of Homeownership. *Journal of Urban Affairs*, 31, 3. p.297(21)
- Santiago, A. M., Galster, G. C., Kaiser, A. A., Roman, A. H. , Grace, R. A., & Linn, A. T. 2010. Low-income Homeownership: Does it Necessarily Mean Sacrificing Neighborhood Quality to Buy a Home? *Journal of Urban Affairs*, 32, 2. p.171(28)
- Seidman, E. 2009. Don't blame the Community Reinvestment Act: homeownership rates and CRA enforcement soared in the 1990s, but sub-prime came later. CRA shouldn't be the scapegoat for the housing meltdown. *The American Prospect*, 20, 6. p.A15(3)
- Silver, J., & Marsico, R. 2009. An analysis of the implementation and impact of the 2004-2005 amendments to the Community Reinvestment Act regulations: the continuing importance of the CRA examination process. *New York Law School Law Review*, 53, 2. p.271-297
- Smith, M. H., & Smith, G. (Dec 2007). Homeownership in an Uncertain World with Substantial Transaction Costs. *Journal of Regional Science*, 47, 5. p.881(16)
- Sungur, E. A.2000. An Introduction to Copulas. *Journal of the American Statistical Association*, 95, 449. p.334
- Turner, T. M. 2003. Does investment risk affect the housing decisions of families? *Economic Inquiry*, 41, 4. p.675(17)
- Turner, T. M, & Luea, H. 2009. Homeownership, wealth accumulation and income status. *Journal of Housing Economics*, 18, 2. p.104(11)

Walden, M. 1983. A Simple Procedure for Evaluating Homeownership as an Investment. *Journal of Consumer Affairs*, 17, p.439-447

Zhao, X., & Zhou, X. 2010. Applying copula models to individual claim loss reserving methods. *Insurance: Mathematics & Economics*, 46, 2. p.290(10)

## Appendix 1: Model Estimates

<i>Levels in 2008</i>			
	location	Variance	Kurtosis
Home Equity	0.0	-59.56	-3.5
Transaction Accounts	7050.2	-2.52	-2.14
Student Loans	10.0	-4.51	1.01
Credit Card Debt	6543.3	-2.59	-0.69
Children	1.9	-1	-0.43
Investments	21867.1	-2.85	0.71
Non Housing Equity	4162.2	8.61	0.13
Borrowing Against the Home	1.0	-48.13	-2.15
Age	8.9	-4.62	-7.69
Education	0.4	-1.54	--
Income	42828.0	-5.09	-5.12

<i>Change 2005 – 2008</i>			
Home Equity	0.0	-56.28	-3.6
Transaction Accounts	19.1	7.26	-0.1
Student Loans	0.0	-59.32	-3.11
Credit Card Debt	34.8	6.82	-0.35
Children	0.0	-55.5	-2.99
Investments	0.0	-59.95	-3.29
Non Housing Equity	930.6	8.86	-0.01
Borrowing Against the Home	0.0	-52.73	-2.55
Education	0.0	-2.57	--
Income	7272.4	9.52	0.75

*Note: Parameter estimates are posterior means from the MCMC simulations with a burnin of 10k and posterior sample of 50k. Variance and Kurtosis parameters are on the log scale. Refer to the manual for the R package "gamlss.dist" for the functional forms of the distributions.*

**Table 2:** Estimates of the marginal parameters

	HE	TA	IV	NRE	CC	SL	H	Age	INC	CLD	ED	BL	HP
Home Equity (HE)	1	0.22	0.07	0.15	0.11	0.04	0.35	0.08	0.29	0.04	0.15	-0.19	-0.16
Transactions Accounts (TA)	0.22	1	0.22	0.17	-0.01	0.05	0.02	0.06	0.39	-0.07	0.19	-0.05	-0.11
Investments (IV)	0.07	0.22	1	0.06	-0.01	-0.01	0.02	-0.04	0.15	-0.06	0.09	0.05	-0.06
Non-Residence Equity (NRE)	0.15	0.17	0.06	1	0.04	0	0.05	0.01	0.13	0	0.06	-0.01	-0.05
Credit Card Debt (CC)	0.11	-0.01	-0.01	0.04	1	0.16	0.18	0.1	0.24	0	0.15	-0.1	-0.12
Student Loan Debt (SL)	0.04	0.05	-0.01	0	0.16	1	0.06	0.21	0.23	-0.03	0.39	-0.02	0.02
Borrow Against Home (BAH)	0.35	0.02	0.02	0.05	0.18	0.06	1	0.07	0.18	0.05	0.09	-0.08	-0.06
Age	0.08	0.06	-0.04	0.01	0.1	0.21	0.07	1	0.33	0.31	0.21	-0.21	-0.05
Income (INC)	0.29	0.39	0.15	0.13	0.24	0.23	0.18	0.33	1	0.05	0.42	-0.18	-0.23
Children (CLD)	0.04	-0.07	-0.06	0	0	-0.03	0.05	0.31	0.05	1	-0.14	-0.17	-0.01
Education (ED)	0.15	0.19	0.09	0.06	0.15	0.39	0.09	0.21	0.42	-0.14	1	-0.05	-0.09
Black (BL)	-0.19	-0.05	0.05	-0.01	-0.1	-0.02	-0.08	-0.21	-0.18	-0.17	-0.05	1	-0.22
Hispanic(HP)	-0.16	-0.11	-0.06	-0.05	-0.12	0.02	-0.06	-0.05	-0.23	-0.01	-0.09	-0.22	1

*Note: Correlations are posterior means from the MCMC simulations with a burnin of 10k and posterior sample of 50k*

**Table 3:** Correlation Matrix from the Multivariate Normal Copula for the “Level” Model

	HE	TA	IV	NRE	CC	SL	CLD	BAH	Age	INC	ED	BL	HP
Dif in Home Equity (HE)	1	0.05	0.02	0.12	0.05	0.04	-0.02	0.09	0.04	0.07	0	0.03	0.03
Dif in Transaction Accounts(TA)	0.05	1	0.14	0.16	-0.01	0.02	0	-0.12	0.05	0.25	-0.03	-0.03	-0.06
Dif in Investments (IV)	0.02	0.14	1	0.03	0	-0.01	0.01	0	-0.03	0.1	-0.01	0.05	-0.04
Dif in Non-Residence Equity (NRE)	0.12	0.16	0.03	1	0.06	0	0.02	0	0.02	0.1	0.01	0	-0.03
Dif in Credit Card Debt (CC)	0.05	-0.01	0	0.06	1	0.01	0.03	0.06	0.06	0.04	0	-0.02	-0.01
Dif in Student Loans (SL)	0.04	0.02	-0.01	0	0.01	1	0	-0.07	0.11	0.13	0.14	0.01	0
Dif in Children (CLD)	-0.02	0	0.01	0.02	0.03	0	1	0.01	0.22	0.07	0	-0.04	-0.08
Dif in Borrowing Against Home (BAH)	0.09	-0.12	0	0	0.06	-0.07	0.01	1	-0.01	-0.03	0	0.01	0.02
Age	0.04	0.05	-0.03	0.02	0.06	0.11	0.22	-0.01	1	0.26	0.09	-0.21	-0.05
Dif in Income (INC)	0.07	0.25	0.1	0.1	0.04	0.13	0.07	-0.03	0.26	1	0.04	-0.05	-0.13
Dif in Education (ED)	0	-0.03	-0.01	0.01	0	0.14	0	0	0.09	0.04	1	0.05	0.03
Black (BL)	0.03	-0.03	0.05	0	-0.02	0.01	-0.04	0.01	-0.21	-0.05	0.05	1	-0.22
Hispanic (HP)	0.03	-0.06	-0.04	-0.03	-0.01	0	-0.08	0.02	-0.05	-0.13	0.03	-0.22	1

*Note: Correlations are posterior means from the MCMC simulations with a burnin of 10k and posterior sample of 50k. "Dif. In" means the 2005-2008 change.*

**Table 4:** Correlation Matrix from the Multivariate Normal Copula for the "Change" Model

## **Appendix 2: Multiple Imputation Description**

### **1 Introduction**

In the current study we use the 2005 wave of the Community Advantage Program Panel Study (CAP) . One challenge that arises in using the 2005 wave of the study is that the data on debt corresponding to a number of important asset categories was not collected. Specifically, we did not collect information on debt related to:

1. Apartment Buildings
2. Investment Properties
3. Land
4. Commercial Properties
5. Vacation Homes
6. Vehicles
7. Timeshares

Since excluding this debt from the calculation of respondents' net worth would bias upward the net worth of respondents who own said assets, we choose to impute the data. Multiple imputation (MI) is used so that (1) the imputed data is arguably an unbiased approximation to the missing data, and (2) so that our estimates account for our uncertainty in the true values of the missing data. A brief review of MI is provided in Section 2, and in Section 3 the details of our use of MI on the CAP data are provided.

## 2 Multiple Imputation: A Brief Review

Multiple imputation is a general-purpose method for statistical inference on data with missing values (Rubin 1987). When certain criteria on the type of missingness are met, multiple imputation provides an unbiased and relatively efficient alternative to the exclusion of incomplete observations and/or variables from the analysis. Most of the following review is drawn from King et al. (2001).

There are three important mechanisms that could be generating the missingness in the data. The simplest case is that the data are missing completely at random (MCAR). If the data are MCAR, then none of the observed data can be used to predict whether or not the data are missing. “An example of an MCAR process is one in which respondents decide whether to answer survey questions on the basis of coin flips.” (King et al., 2001, pp. 50-51). If missing data are MCAR, estimates are unbiased if the observations with missing data are omitted, but estimates are still more efficient if MI is used. Data that are missing at random (MAR) are missing in a way that depends on observed data (e.g. individuals with small incomes are less likely to report their credit card debt). If the missing data is MAR, deleting observations with missingness produces bias and reduces efficiency of estimates. MI can eliminate bias and improve efficiency with MAR missingness. The last case is that the missingness is non-ignorable (NI), which means the probability of missingness depends on the unobserved value of the data (e.g. high income people are less likely to report their income). In the case of NI missingness, the MI

approach reviewed here is not appropriate, and more advanced techniques must be implemented to estimate parameters in an unbiased and efficient manner.

The first step in multiple imputation is to posit a probability distribution for the missing data. This usually proceeds by regressing the observed values of the variables with missingness on the other observed variables and using that regression model as the distribution for the missing data. Suppose the observed data consist of the dependent variable, a matrix of independent variables ( $\mathbf{X}$ ), and a variable with some missingness ( $Z$ ). A common approach to specifying the distribution of the missing parts of  $Z$  is to estimate the linear regression model

$$Z_{obs} = \beta' \mathbf{X}_{obs} + \gamma Y_{obs} + \epsilon.$$

This model implies that the distribution of the  $i^{\text{th}}$  missing observation is

$$N(\tilde{\beta}' \mathbf{X}_{obs}^{(i)} + \tilde{\gamma} Y_{obs}^{(i)}, s_{\epsilon}^2),$$

where  $\{\tilde{\beta}, \tilde{\gamma}\} \sim MVN(\{\hat{\beta}, \hat{\gamma}\}, \Sigma_{\{\beta, \gamma\}})$ . Different models for the missing data can be used, and are often appropriate, especially when the unobserved data is asymmetric, multi-modal, bounded and/or discrete. After the distribution of the missing data has been specified, the next step is to draw many imputations – usually 5 to 20 – for the missing data from its distribution. Given  $k$  imputations, the analyst then forms  $k$  complete datasets

by substituting the imputed values for the missing values. Then analysis proceeds by estimating all quantities of interest (e.g. mean, median, regression coefficients) on each of the  $k$  datasets as if each were completely observed. For the  $j^{\text{th}}$  parameter of interest ( $\theta_j$ ), this will result in  $k$  estimates of the parameter  $\{\hat{\theta}_j^{(1)}, \hat{\theta}_j^{(2)}, \dots, \hat{\theta}_j^{(k)}\}$  and  $k$  estimates of the standard error  $\{\hat{s}_j^{(1)}, \hat{s}_j^{(2)}, \dots, \hat{s}_j^{(k)}\}$ . These are combined to get a single estimate for  $\theta_j$  and a standard-error of that estimate  $s_j$ . The estimate of  $\theta_j$  is given by

$$\hat{\theta}_j = \frac{1}{k} \sum_{i=1}^k \hat{\theta}_j^{(i)},$$

and the standard error is

$$s_j = \sqrt{\frac{1}{k} \sum_{i=1}^k \left(\hat{s}_j^{(i)}\right)^2 + \left(1 + \frac{1}{k}\right) \frac{1}{k-1} \sum_{h=1}^k \left(\left(\hat{s}_j^{(h)}\right)^2 - \frac{1}{k} \sum_{i=1}^k \left(\hat{s}_j^{(i)}\right)^2\right)^2}.$$

The combined estimates can be used as if they were computed once on a complete dataset, as one would usually manipulate estimates and standard errors to form z-statistics, p-values, confidence intervals, etc.

### 3 Imputation of the CAP 2005 Debt Data

With the CAP data, the debt variables that are missing in 2005 were measured in 2008. We assume the data are MCAR.<sup>6</sup> We estimate the imputation models for the debt variables on the 2008 data, and use these models for MI with the missing 2005 data.

The imputation models we use are quite simple. We experimented with many models, but according to the cross-validated loglikelihood – a common predictive measure of model fit (Hurvich, 1985; BeltraTo and Bloomfield, 1987),<sup>7</sup> the best model for imputation simply uses the corresponding asset level and either the logarithm or square-root thereof to impute the level of debt. The specific regression model used for the imputation is a negative-binomial form. The negative-binomial is appropriate because the data are measured in dollars such that the debt variables are non-negative discrete outcomes (King, 1989). The probability mass function of the missing debt ( $y$ ) for the  $i^{\text{th}}$  observation is

$$\frac{\lambda_i^y}{y!} e^{-\lambda_i},$$

---

<sup>6</sup> Since the data are missing as a result of survey design, it may even be appropriate to assume MCAR, but since there is a temporal dimension to the missingness, we concede the possibility of a trend in acquisition of assets and the resulting debt.

<sup>7</sup> It is important to note that we need only be unbiased in the imputation model to produce unbiased results. Given that it is an unbiased model, the explanatory power only serves to improve the efficiency of estimates.

where  $\lambda_i = \exp(\beta_0 + \beta_1 Asset_i + \beta_2 f(Asset_i) + \gamma_i)$ ,  $f(\cdot)$  is either  $\ln(\cdot)$  or  $\sqrt{\cdot}$ , depending on the particular debt category and  $\gamma_i \sim \Gamma(\frac{1}{\eta}, \eta)$ . The parameter  $\eta$  is an extra-Poisson variance parameter and accounts for over-dispersion in the debt variables.

The parameters of the regression models are presented in Table 5. Package Zelig (Imai, King and Lau, 2008) in the R statistical programming language (R Development Core Team, 2009) is used to estimate the imputation models and draw the imputations.

Dependent						
Variable	Intercept	SE	Asset	SE	f(Asset)	SE
			-			
Apartment		2.91	5.98E-	8.55E-		
Buildings	-2.42	E-02	07	09	1.18	2.54E-03
Investment	1.26E+0	1.62	1.38E-	6.78E-		
Property	1	E-03	06	10	-1.15E-01	1.46E-04
	-		-			
	2.73E+0	6.78	1.23E-	1.82E-		
Land	0	E-03	06	09	1.16E+00	6.02E-04
Commercial	1.37E+0	1.12	2.60E-	2.34E-		
Property	1	E-03	06	09	-2.51E-01	1.46E-04
	-					
	3.77E+0	2.28	4.75E-	6.96E-		
Vacation Homes	0	E-02	07	09	1.23E+00	2.01E-03
			-			
	5.62E+0	1.48	7.09E-	6.24E-	3.62E-	
Vehicles	0	E-03	05	08	02*	1.96E-05

\* The  $f(\text{Asset}) = \sqrt{\text{Asset}}$ , otherwise  $\ln(\text{Asset})$

**Table 5:** Imputation Model Estimates

Table 6 gives some summary statistics for the imputation process. These include the number of observations for which there was missing data (i.e. an asset was owned, but no debt reported) in 2005, the number of observations from 2008 used to train the imputation model, and a likelihood ratio test of the improvement in model fit from adding the Asset and  $f(\text{Asset})$  to the model with just an intercept.

Variable	N-Missing	N- Training	LR-Test
Apartment Buildings	9	15	1,369,559*
Investment Properties	49	116	2,607,109*
Land	114	276	7,959,575*
Commercial Properties	6	20	2,508,836*
Vacation Homes	18	31	3,679,408*
Vehicles	1,757	2,862	15,512,315*

\*Statistically significant at the 0.05 level

**Table 6:** Additional Imputation Model Details