Technology is Making Preventive Servicing Even Smarter: But the Affordable Lending Sector is Lagging

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Abstract

This paper documents the growing importance of preventive servicing—business practices that emphasize early intervention in delinquency and default management practices that also help financially troubled borrowers avoid foreclosure—and suggests that the loan servicing side of the affordable housing delivery system may be under-appreciated and undercapitalized.

We test several preventive servicing-related propositions using a database of more than 18,000 affordable housing loans, and find that within this universe of loans, controlling for loan and borrower characteristics, the likelihood that a delinquent mortgagor will ultimately default varies significantly across loan servicers.

Keywords: mortgages, servicing, default, affordability

Introduction

Favorable demographics, unparalleled economic growth, and low interest rates combined with an aggressively supportive public policy environment propelled homeownership rates upwards during the 1990s to an historic high of 69 percent in 2004, with "households of all ages, incomes, races and ethnicities joining in the home buying boom." (Joint Center for Housing Studies 2005). HMDA records verify an impressive increase in mortgages to low- and moderate-income (LMI) families – 38 percent between 1993 and 1997, compared with 27 percent growth for loans to higher income households (Quercia, McCarthy, and Wachter 2003, 31). This growth in mortgages to LMI households was supported by the widespread introduction of "affordable" mortgage products featuring flexible underwriting—including low down payments, higher debt ratios, and reduced cash reserves—combined with the use of nontraditional means of verifying creditworthiness (Quercia et al. 2002).

What a robust economy and liberalized underwriting make possible, an economy in decline can diminish. As the 2001 recession took hold and was followed by a "jobloss" recovery, the number of financially stressed families grew, so that the number of home*owners* with critical housing needs increased by 1.2 million (78 percent) between 1997 and 2003 (Lipman 2005). Such high housing costs among LMI homeowners, who are particularly sensitive to even modest declines in the demand for labor, inevitably lead to more volatile payment patterns than characterize mortgaged homeowners as a whole. This helps explain why default rates for more flexibly underwritten, higher loan-to-value government backed loans tend to be significantly higher than those for conventional mortgages as a whole (HUD 2003, Table 18).

Efforts to increase the rate of homeownership can only be successful to the extent that homeownership is sustainable. According to a recent HUD study, "policies that promote only temporary spells of homeownership will have little impact on the national homeownership rate. What is important is promoting new ownership spells that are sustainable" (HUD 2004b, p.v).

If the 1990s was the decade of affordable homeownership, then current economic realities suggest that the "new frontier in successful lending in low- and moderate-income communities just may be in post-purchase services" (Meyer 1997). These services include collections and default management strategies designed to keep delinquent homeowners from losing their homes through foreclosure. This paper suggests that with the proliferation of affordable lending products, which layer mortgage default risks, the servicing side of the affordable housing system has become more critical than ever. After discussing what we mean by preventive and smart servicing, and reviewing the economics of the loan servicing business, we empirically test several servicing-related propositions using a database of more than 28,000 affordable housing loans and payment records collected as part of a multiyear evaluation the authors are conducting of an innovative secondary mortgage market demonstration called the Community Advantage Program (CAP).

Preventive and Smart Servicing

In this paper, we use the term "preventive servicing" to describe delinquency management practices that emphasize early intervention and default management practices that help financially troubled borrowers avoid foreclosure (Oliver et al. 2001, 32). For a full discussion of alternatives to foreclosure, see Cutts and Green (2005). "Smart servicing" means technologies that enable preventive servicing, including "modeling software and scripted menu options to engage collector and borrower." (Fields 2001, 27). In the effective management of non-performing loans, collections efforts are supported by smart systems that prioritize collections calls and identify loss mitigation pathways appropriate to each case.

The key to effective and efficient preventive servicing is in knowing which borrowers to contact when, and success often depends on early intervention. For example, in a 2001 review of FHA loans, one servicer experienced a greater than 45 percent success rate for workouts processed within the first two months of delinquency, but only a 10 percent success rate if the workout was processed after seven months (HUD Audit Report 2002). While quick intervention is key to preventive servicing, engaging the borrower is sometimes easier said than done. As a case in point, in an effort by Countrywide Mortgage to help 300 seriously delinquent Chicago-area homeowners avoid foreclosure, only 38 responded (Sichelman 2001, 18). Frustrated by such low response rates, the company sent circuit riders to meet with 61 borrowers, and "despite the fact that 32 of these customers were in the late stages of foreclosure, Countrywide was able to create repayment programs for 59 of the residents." (Mozilo 2000, 18), dramatically underscoring the power of preventive servicing.

Smart Servicing and the Economics of Affordable Mortgages

As a rule, smart and preventive servicing makes good business sense because of the high cost of defaults, especially in the case of affordable lending because LMI borrowers typically have little financial cushion to fall back on in the event of economic setback (Baku and Smith 1998), while the liberalized underwriting guidelines featured in many affordable lending programs increase default risk (Steinbach 1995).

Though most conventional or affordable mortgage defaults do not end in foreclosure, those that do can be quite costly. For example, Cutts and Green (2005, 352), citing Focardi's data, note that "for a sample of loans that went through the full formal foreclosure process, the total cost, including lost interest during delinquency, foreclosure costs, and disposition of the foreclosed property, ran $58,759 and took an average of 18 months to resolve, while voluntary title transfer alternatives to foreclosure had average costs in excess of $44,000 and took nearly one year to conclude." In a 1996 article, Ambrose and Capone illustrated how in rising markets "savings to the mortgage investors and insurers from preventing one foreclosure (a successful workout) are large enough to pay the added costs of four workouts," and that even in softer markets where prices are declining by as much as 5 percent a year, one successful workout could offset the costs of more than two additional workouts (cited in Capone and Metz 2003, 10). Since typical CRA loans with smaller equity cushions are more likely to default and result in greater loss severity for the investor or insurer, this cost benefit equation should be even more compelling for the affordable segment.

The costs of default are borne largely by the holders of credit or default risk (e.g., Fannie Mae, Freddie Mac, FHA, and Mortgage Insurers); thus, they stand to benefit the most from the use of smart and preventive servicing. Because the servicer has the relationship with the borrower, however, the investors and insurers must look to the servicer to implement these loss-minimizing servicing practices, which are often labor intensive and/or require investments in new technologies and training.

Servicer economics, on the other hand, are reliant on maximizing efficiency, with technology, scale economies, and profit growth driving consolidation: between 1989 and 2005, the share of the market among the five largest servicers went from 7 percent to 42 percent, with the largest 25 servicers holding 69 percent of the market (Inside Mortgage Finance Publications, 128, Inside Mortgage Finance 2006). In the drive to economies of scale, productivity gained significantly, from around 700 loans serviced per direct full-time employee in 1992 to 1,229 in

2000, an increase of about 60 percent in less than ten years. Direct servicing costs per loan were shaved from $80 to $90 per loan in the late 1980s to less than $50 per loan in 2000. (Oliver et al. 2001).

On the revenue side of the servicing equation, the largest single source of revenue is servicing fees. The standard servicing fee for conventional conforming home loans is one quarter of one percent (25 basis points) of the outstanding balance of the loan. On government-backed loans the fee is generally 44 basis points (Muolo 2000), a reflection of lower average loan balance, greater reporting requirements, and higher costs associated with servicing FHA and VA loans.

The Special Case of Affordable Housing Loans

Our literature review found few empirical studies of the economics of servicing "affordable" mortgage portfolios—those characterized by below-average loan balances and disproportionately large numbers of low- and moderate-income borrowers, but there are scattered indications of the special challenges posed by this market segment from the existing research and examination of the CAP portfolio.

Almost 30 years ago, the relationship between average loan size and discounted, net servicing revenue was found to be positive and nonlinear (McConnell 1976, p. 442). In 2001, the average conventional mortgage loan balance was $120,393. With the average balance of Self-Help's Community Advantage loans being a significantly lower $79,800, the average CAP loan generated 34 percent less servicing fees than the average conventional loan ($200 vs. $301). Late fees generated by increased incidence of delinquency may offset this latter differential somewhat.[1] More recently, Linda Simmons, a Stratmor Group partner, analyzed a large pool of mortgage data from 1999–2002 and found "a strong relationship between portfolio composition and servicing costs" (DeZube 2003, 48). Stratmor Group found conventional conforming loans cost an average of $48 a year for core servicing over the study period, "while government-backed loans came in at $98." Borrowers of affordable conventional loans have loan sizes and risk profiles more like those of government-backed borrowers, and may therefore have similar economics.

On the positive side, it has been suggested that affordable mortgages exhibit slower and less volatile prepayment patterns. In their analysis of prepayment rates associated with pools of FHA-insured loans, Deng and Gabriel (2002) found that borrowers with lower credit scores and higher default risks were less likely than higher credit quality borrowers to prepay. By tracking Freddie Mac loans purchased from 1993 to 1997 through the end of 1999, Van Order and Zorn (2004) found that mortgage loans to low income and minority borrowers prepay less rapidly under conditions favorable to refinancing, particularly among minority borrowers. If indeed CRA mortgages prepay slower than other types of conventional mortgages, their servicing revenue stream will be longer and potentially more valuable.

To summarize, the business challenges with servicing mortgage loans originated largely for CRA credit are compounded by their smaller loan size and higher delinquency and default rates. Although these challenges may be offset to some extent by slower prepayment patterns, the mortgage servicing industry needs to implement the most efficient possible default

[1] Late fees, incurred for payments received after the 15th of the month, are typically 3 percent to 5 percent of the payment (sources include http://www.californiarealestatecenter.com/mortgage-payment-behind.htm; http://www.mortgagenewsdaily.com/trackback/?i=171)

management systems to keep costs down while meeting investor requirements. It is in the development of smart servicing tools that investor/insurer and servicer goals might be aligned, consistent with the public policy goal of sustaining homeownership.

The Evolution of Smart Servicing[2]

The application of advanced information technologies to collection management first took place in the credit card industry during the early 1990s as the percentage of individuals making minimum or no monthly payments swelled along with aggregate debt levels. This sector was a ripe testing ground for decisioning systems that analyze the behavioral patterns of delinquent cardholders and determine who was least likely to pay without early intervention (Waggoner 2002).

In a parallel fashion, the first generation of automated mortgage servicing models, introduced in the mid-1990s, identify delinquent mortgage accounts that are likely to benefit most from early interventions. These tools, such as Freddie Mac's Early Indicator (EI) and Fannie Mae's Risk Profiler (RP) use a combination of borrower information contained in the mortgage application, loan-specific payment patterns, and the borrower's updated credit information. Personal contact with the delinquent borrower is not required to produce a propensity score (Stanton 2001). This approach, which optimizes servicers' collection budgets by prioritizing call schedules, is only the first part of smart mortgage servicing systems.

The second phase of smart mortgage servicing applies a combination of scripting systems such as Freddie Mac's Early Resolution, to aid servicers when they contact borrowers, and analytic tools such as Genworth's Loss Mitigation Optimizer, Freddie Mac's Workout Prospector, and Fannie Mae's Workout Profiler to process information to assess the viability of

[2] This section is based largely on a draft prepared for this project by Steve Hornburg.

foreclosure alternatives for each case. These tools essentially apply consistent underwriting methodology to keeping borrowers in their homes by assessing what one industry expert refers to as the “three C’s” of capacity, collateral, and commitment.

Since investors and insurers stand to gain the most from aggressive loss mitigation, they were often the catalysts for the initial introduction of utilities and technology in this area, and invested heavily in them. Today, these tools are increasingly being developed and/or enhanced by third-party, software companies and are being integrated more directly into the servicers’ systems. [3](source: Kehr) While many of these tools go hand in hand, they can be used independently, and on mortgages of many different types.

FHA is committed to preventive servicing as well, launching its own loss mitigation program in 1996. By 2005, FHA officials affirmed their belief that “[the loss mitigation program] is becoming the dominant approach to address a default” (National Mortgage News 2005b). The cost effectiveness of preventive servicing is evident. In 2002, FHA paid out $5.5 billion in claims on 64,000 foreclosures, while paying just $98 million to help keep 73,000 financially troubled borrowers in their homes with recast loans (Harney 2002). By 2005, the number of loss mitigation claims paid rose to 90,000 resulting in FHA avoiding an estimated $2 billion in losses (National Mortgage News 2005b).

Instead of developing its own tools, FHA relies on servicers to apply commercially available smart servicing tools to their FHA loans, and has instituted a system of scoring servicers and providing financial incentives for loss mitigation performance ($27 million in 2005), (National Mortgage News 2005). FHA is not the only investor to score or pay servicers for using foreclosure alternatives. Freddie Mac’s Servicer Performance Profiles benchmark

[3] Debbie Kehr, Director of Servicing Operations at Fannie Mae, phone interview by author, 30 August 2005.

servicers using such indicators as cure rates, workouts, and foreclosure timeliness (Melchiorre 1999). One servicer reported earning $25,000 per month through loss-mitigation incentives (O'Connor 2003). Financial incentives have led some servicers to see their "loss mitigation departments move from cost centers to profit centers" (HUD Audit Report 2002, 3).

Evidently, smart and preventive servicing has been effective for investors and insurer, and even servicers. But how effective have they been in sustaining homeownership? Through aggressive outreach featuring a combination of preventive and smart servicing, Fannie Mae and its loan servicing partners helped nearly 34,000 financially-strapped borrowers avoid foreclosure in just 2004; more than 92 percent received workouts that allowed them to stay in their homes.[4] From 1996 to the present, Fannie Mae's workout ratio rose from 32 percent to 52 percent, while Freddie Mac's rose from 26.4% to 38.2% and the number of FHA workouts increased some seven-fold (Cordell 2001, Cornwell 2003, Kehr 2005[5];). GE's mortgage insurance company reported almost doubling its cure ratio after introducing its Loss Mitigation Optimizer (Venetis 2001). One servicer reported a 50 percent increase in FHA and VA workouts after implementing EI on those loans (Abraham 1999); another claims a tripling for workouts in the initial period after implementing 'BackInTheBlack' loss mitigations system (O'Connor 2003). From 2000 to 2004, 145,000 Freddie Mac borrowers, or "130 families every business day" were kept in their homes through loan modifications, repayment plans, and forbearance. (National Mortgage News 2005, p. 1)

Perhaps the clearest evidence comes from Cutts and Green's 2005 examination of Freddie Mac-owned loans that went 60- to 120-days delinquent between January and September 2001. Following these loans for 18 months, they found that the use of a repayment plan lowered

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[4] Kehr, 2005
[5] Ibid.

the probability of failure by 80 percent for non-LMI borrowers and by 68 percent for low- to – moderate-income borrowers.

Clearly, then, these technologies and tools have had an impact on the way non-performing mortgages are serviced, and on the ability of servicers to cost-effectively keep more borrowers in their homes.

Exploring Servicing Issues Using Data from The Community Advantage Secondary Market Demonstration Program (CAP)

In this section, we use a unique dataset of more than 28,000 mortgages made to LMI borrowers to explore the impact of various factors on delinquency transitions (from delinquent to seriously delinquent or to cure), and attempt to isolate the effects of servicing. A similar analysis conducted by a large servicer examined delinquency transitions—from current to delinquent, from delinquent to foreclosure or to cure, and from foreclosure to cure—within subprime loans (Sjaastad et al. 2005). By examining 23,000 subprime, loan level transitions over nearly four years from several different servicers, the analysis validates the predictiveness of such factors as FICO score, LTV, seasoning, and payment history for each transition type. After controlling for these factors as well as for different servicers, Sjaastad et al. conclude that the results "suggest that servicers can have specific, strong impacts on transition rates and delinquency duration times" in subprime mortgages (2005, 16).

The Community Advantage Secondary Market Demonstration Program, or CAP, is a multibillion-dollar initiative designed to expand home ownership opportunities for credit-worthy low-income, low-wealth individuals who are not effectively served by the conventional market. CAP is a partnership among the Ford Foundation, the second largest foundation in the United States; the Center for Community Self-Help, a North Carolina-based community development organization; and Fannie Mae, the nation's preeminent secondary mortgage market facility. CAP's goal is to provide tangible evidence that low-wealth borrowers are "bankable" and that Fannie Mae (and Freddie Mac) can significantly expand their purchase of affordable housing loans without compromising either their balance sheet or their concerns over safety and soundness.

With a Ford Foundation grant to underwrite a significant portion of the credit risk, Self-Help purchases affordable mortgages (i.e., CRA loans) that could not otherwise be readily sold in the secondary market because of their perceived higher risk attributes, and sells them to Fannie Mae while retaining full recourse. Self-Help contracts with participating mortgage lenders to originate and subservice the loans.

CAP mortgage products feature flexible underwriting and typically include one or more of the following features: low or no down payment, lower reserves, higher debt-to-income ratios, borrowers with spotty credit records or no established credit, and waiver of private mortgage insurance.

Data for our analysis come from 28,131 loans to LMI borrowers that Self-Help purchased prior to January 1, 2003, with an average original balance of $79,800. For each loan, the data include a full set of loan characteristics, some borrower characteristics, and the complete payment history from the time that Self-Help purchased the loan.[6] The loan database is being compiled as part of the authors' on-going multi-year evaluation of CAP designed to (1) measure loan performance by tracking delinquency, default, and foreclosure rates over the critical first

[6] There are a small number of missing months in the payment history file. We have data on 580,276 loan-months, with 532 loan-months missing. Using an algorithm, we fill in likely values for the missing months. For example, if month 1 was paid on time and month 3 was paid on time, we assume month 2 was paid on time; similarly if month 1 was paid on time but month 3 shows a 60-day delinquency, we assume month 2 was late. In the few instances where a precise determination was not possible, we imputed months such that any delinquency spell would be as short as possible.

five years of the mortgage term; (2) document the social and economic impacts of homeownership on borrowers, and (3) assess to the extent practicable the impacts of CAP on neighborhood conditions and housing market dynamics. As part of the evaluation, we have begun to build the CAP survey, a five-year panel survey of over 3,500 CAP homeowners. Some of the descriptive data cited later in the paper is from our baseline interviews of panel members.

Who Are the Homeowners?

Almost 40 percent of CAP borrowers are people of color, 44 percent are women, 16 percent single parents,[7] 19 percent live in non-metropolitan areas, and most importantly, half had incomes below 60 percent of the local median household income when they closed on their loans (Table 1). Moreover, nearly 50 percent of all CAP families had FICO scores of less than 660, or no credit score at all. Compared with borrowers whose conforming loans were bought by Fannie Mae in 1999, CAP homeowners are about twice as likely to be people of color, almost five times more likely to have incomes below 60 percent of area median, and two and a half times more likely to be female.[8]

Using data from our baseline survey of over 3,727 CAP homeowners, we can look at the family and employment situations of these borrowers in greater detail.[9] As a rule, CAP families have strong commitments to the work force, with two wage earners in more than three quarters of all sampled households with married couples or partners. Sixteen percent of all borrowers and 10 percent of all spouse/partners that work hold more than one job, including part-time, weekend, and evening work. Ninety-six percent of our surveyed borrowers work at least full

[7] This figure is an estimate for the entire population of CAP borrowers based on the baseline survey of the Panel.
[8] The Center for Community Self-Help. "Comparison of Self-Help Borrowers with Those for Conforming Loans Purchased by GSEs." Durham, NC.
[9] The CAP homeowners' baseline survey occurred generally around 12 to 24 months after home purchase.

time (35 or more hours per week) and almost 30 percent average at least 50 hours of paid work per week.

Despite the fact that our interviews were conducted in the midst of the economic slowdown, we found low unemployment rates among all borrowers (3.1 percent) at the time, although much larger numbers of borrowers (16.8 percent) and their spouses/partners (59.3 percent) had experienced at least one spell of joblessness lasting a week or more since closing on their loans (Table 1).[10] Because a greater percentage of surveyed black households (60 percent) than whites (41 percent) consists of single adults (with or without children) and just one wage earner, they are more sensitive to even modest declines in the economy and more likely to experience declines or slower growth in income during an economic slowdown.

Thus, for example, while the median income of white CAP borrowers increased by more than 20 percent, to $37,500 between 12 and 18 months after closing, the median income of black households increased by just 8 percent, to around $32,500. This means that the relative income deficit of blacks, which was just $1,000 at closing ($30,150 vs. $31,200 for whites), grew five-fold in just 18 months or less.

The phenomenon of high labor market volatility and job churning among LMI borrowers during periods of economic decline, characterized by cutbacks in overtime and loss of second jobs and paid spousal work, contributes to higher rates of late and missed mortgage payments among all LMI families; however, those with single wage earners are particularly affected. Because LMI families are more likely than others to lose income intermittently from periodic job cutbacks and layoffs, they are also more likely than higher income borrowers to fall behind in their loan payments and have a harder time catching up. This puts even more pressure on servicers whose portfolios contain large numbers of affordable mortgages. This is why

[10] Post-purchase joblessness among spouses includes those who are not in the labor force.

technology that enables servicers to identify which borrowers are most likely to fall farther behind once they miss a single loan payment can be a very valuable default management tool.

The Delinquency Experiences of CAP Borrowers

As of March 2005 in the CAP portfolio, about 2 percent of all loans had reached foreclosure. Among loans that went at least 30 days delinquent, only 10 percent eventually reach foreclosure, while almost 30 percent of loans that went 60 days or more delinquent reached foreclosure, and for those going 90+ days late, more than 40 percent were foreclosed.

Because this paper deals with servicing and default management rather than with origination and the assessment of initial credit risk, we are most interested in examining the outcomes of CAP loans once they become at least 30 days past due than we are with determining the factors that cause loans to become delinquent in the first place. Since the rate of failure from a 90+ day delinquency is more than four times that of a failure from a 30-day delinquency, we focused on the transitions within this period. From the payment history, we were able to identify when a loan was 30 (or 60) days delinquent. This generated a "30-day delinquency spell," which could have three outcomes: the delinquency was "cured" (i.e., the borrower caught up on the missed payments), the delinquency progressed to a 90-day delinquency (i.e., default), or the delinquency was still active at the end of the observation period, (either due to the borrower making only enough payment to remain in the same status or improving from a 60-day to a 30-day delinquency, or progressing from a 30-day to a 60-day delinquency). Once a loan was cured, any subsequent 30-day delinquency generated a new spell. An observation was considered cured if the loan was paid off while still 30 to 60 days delinquent.[11]

[11] We examined the number of delinquencies that ended in repayment, to make sure there were not a large number of early stage delinquencies driven by pending refinancing plans. However only 234, or 1.5 percent, of 30-day spells ended in payoff.

For the purposes of this study, we looked at all 30-day delinquency spells that began between September 1998 and December 2003 (N=15436). If necessary, we followed spells through December 2004.[12]

Just because LMI borrowers as a group may experience greater delinquency and default rates than higher income mortgagors does not mean that all, or even most, of the former have spotty payment records. In fact, through December 2004**,** 79 percent of the 28,131 CAP borrowers had never missed a monthly payment, while another 15 percent were never more than 60 days late in making their mortgage payment (Table 2).

The servicing challenge associated with affordable lending can be more graphically illustrated by the number of separate 30-day delinquency spells during the study period (Table 3). 5,969 of the 28,131 CAP borrowers were late 30 days or more at least once; of those, 2,564 or about 43 percent had only one delinquency spell, lasting an average of 2.5 months before curing or defaulting. The remainder of the "ever delinquent" pool—about 12 percent of all CAP borrowers—experienced two or more separate delinquency spells. This includes 1,403 repeatedly delinquent borrowers with four or more delinquencies. While accounting for about 5 percent of all borrowers, this group generated over half of all delinquency spells. Together, these 5,969 borrowers generated 15,436 delinquency spells, of which 2,200 or 14 percent ended in default which we define as being 90 days late or in foreclosure.[13] (Table 4). These 2,200 'defaults' represent 7.8 percent of all loans tracked and 31 percent of all ever delinquent loans (from Table 2). The other 69 percent of ever-delinquent loans never proceeded beyond 60 days late. Interestingly, the small group of serially delinquent borrowers are not necessarily much

[12] Since most delinquencies have an outcome within 6 months, this meant that right censoring (i.e. a spell not achieving an outcome prior to the end of the observation period) was a minimal problem in these data.
[13] We use 90 days as a proxy for default, because completed defaults usually lag substantially, and the data provides a greater number of 90+ delinquency occurrences. The measure, then, is to what extent loans move to the more severe category of 'serious delinquency' or 90+ days late.

more likely than other late payers to go into default. While about 13 percent of all borrowers experiencing their first delinquency spell default, this is true for almost the same share (13.6 percent) of all borrowers with 5 or more delinquency spells. This illustrates what many smart servicing technologies have identified—that some borrowers are frequently delinquent without posing a higher default risk.

In fact, not only have the vast majority of CAP homeowners never missed a payment, but 83 percent of all 15,436 delinquency spells cure (Table 5). Of the 17 percent of all delinquency spells that were not cured, the vast majority went into default, with a very small number remaining 60-90 days late, neither catching up nor falling further behind.

Our goal in modeling the outcomes of the 15,436 delinquency spells is to identify predictors of the likelihood that a given delinquency will be cured or worsen and go into default. This requires survival analysis within a competing risk (i.e., multiple possible outcomes for a spell) and repeated events (i.e., the same loan could contribute multiple spells to the analysis) framework.

We reflect the competing risks of prepayment and default using a multinomial logit model. Allison (1984; 1995) shows that the logit model, with data restructured such that each month a loan is active supplies an observation, produces the same likelihood function as a proportional hazards model with time treated as discrete. The multinomial logit model treats the outcome as polytomous and, via the restriction that the sum of the probabilities of each outcome must equal one, controls directly for competing risks, i.e., the increase in the probability of one outcome necessitates a decrease in the probability of at least one competing outcome. Formally, the log-likelihood function is defined as:

$$\ln L = \sum_{t=1}^{T} \sum_{i=1}^{n_t} \sum_{j=0}^{2} d_{ijt} \ln(\Pr(y_{it} = j))$$

$$\Pr(y_{it} = j) = \frac{e^{b_j Z_{it}}}{1 + \sum_{k=1}^{2} e^{b_k Z_{it}}} \quad for\ j = 1,2$$

$$\Pr(y_{it} = j) = \frac{1}{1 + \sum_{k=1}^{2} e^{b_k Z_{it}}} \quad for\ j = 0$$

where d_{ijt} is an indicator variable taking on the value 1 if outcome j occurs to loan i at time t and zero otherwise.

The multinomial logit model has several advantages over a proportional hazards model: competing risks are handled easily with no assumption of proportionality; the model can be estimated with commercial software; and the restructuring of the data into loan-months facilitates the inclusion of time-varying covariates. The model, however, assumes the "independence of irrelevant alternatives," which means that the odds ratio for any pair of outcomes should be independent of any alternative outcomes. This model also assumes that outcomes at any one point in time are independent of outcomes in any previous point in time. See Clapp, Deng, and An (2004) for a more extensive discussion of the choices available for modeling the competing risks of mortgage loan outcomes. To control for the potential statistical problems associated with repeated events, the model was estimated using Stata's *mlogit* procedure (Stata Corporation 2002) with an adjustment to the standard errors for clustering by loan.[14]

To test for differences among lenders/servicers, we incorporate into our survival model dummy variables for the CAP lender/servicers with at least 600 delinquencies over the study period.

Control variables in the model include:

[14] Such a correction also helps correct for unobserved heterogeneity (Allison 1995).

- Loan characteristics: credit score dummy variables, including a dummy for no credit score; a dummy for back-end ratios >37 percent; a dummy for loans with an LTV of 97 percent or greater; and loan age at the time of delinquency.
- Borrower characteristics: dummies for gender and race/ethnicity; income as a percent of Area Median Income (AMI); and a dummy for first-time homebuyer status.
- Macroeconomic conditions: To help separate lender/servicer effects from regional economic effects, we include dummy variables for the states with the most loans: North Carolina, California, South Carolina, Virginia, Oklahoma, Ohio, Georgia, Mississippi, and Illinois (Refer back to bottom panel of Table 1).

We want to determine to what extent the outcomes of 30-day delinquencies are affected by the loan servicer. In the Community Advantage Program, most lenders are servicing the loans themselves.[15] Consequently, there is a one-to-one correspondence between lenders and servicers, so we reference lender in our analyses.

Our model analyzes the number and outcomes of 30-day delinquencies for seven of the largest CAP lenders who together comprise 65 percent of the 28,131 loans tracked and 82 percent of the 15,436 delinquency spells.[16] Lenders 1, 5, and 6 have rather low cure rates while Lenders 2, 3, and 4 have higher than average cure rates (Table 6). These are accompanied by quite high default rates for Lenders 1, 5, and 6 and lower default rates for Lenders 2, 3, 4, and 7.

[15] One lender had 2 subservicers, but because the smaller of these serviced only 6 percent of the delinquencies in that group of loans, and because both subservicers had better than average cure rates and nearly identical default rates, we lump these loans together.

[16] Lenders were chosen for inclusion in our analysis based on having 600 or more delinquencies, not the number of loans, so these represent "some of" the largest lenders in the program.

However, these differences may be due to differences in the composition of each lender's loan portfolio—i.e., some lenders may have more high-risk loans than others. Consequently, we estimated the survival model, controlling for various loan and borrower characteristics. Because of the complexity of the model and the relatively high co linearity among some of the variables, the estimation was very sensitive, and we have included in this paper a trimmed model featuring the most significant predictors.

Tables 7 and 8 present the results of the survival model. We specify a multinomial logit model to estimate the probability of being cured and the probability of going into default relative to staying 30-days to 60-days delinquent. A positive coefficient means that the odds increase as the independent variable increases; a negative coefficient means the odds decrease. So, for example, in Table 7 the odds of a borrower with an original credit score of 620 or less curing a delinquency is just 5 percent lower than for a borrower with a higher credit score, all else equal. Tables 7 and 8 also show the costs associated with chronically delinquent borrowers as, on average, those with more previous delinquencies are significantly less likely to cure.

Of primary interest is the fact that, after controlling for loan and borrower characteristics, and geography, a proxy for regional economic conditions, we find significant differences in the cure rates among lenders (the omitted category is "other lenders"). Specifically, 30-day delinquencies for Lenders 1, 5, and 6 are significantly less likely to cure as they are for other lenders, while 30-day delinquencies for Lenders 3 and 7 are significantly more likely to cure in comparison to other lenders. The greatest contrast is between Lenders 1 and 3. A 30-day delinquency for Lender 1 is only 51 percent as likely to be cured as the other lenders, while a 30-day delinquency for Lender 3 is 45 percent more likely to be cured. Interestingly, we find fewer significant variables in the default equation (Table 8). Notice that the delinquency spells of chronically delinquent borrowers are also less likely to result in default (6 percent less likely). Among lenders, we find that Lenders 2, 3, 5, 6, and 7 have significantly higher rates of default.

Above and beyond the higher monthly default rates of delinquencies for some lenders, the competing risks complicate the analysis of cure and default rates over time. The pool of delinquencies at risk for going into default will decrease much more quickly for lenders with higher cure rates, leading to lower default rates over several months.

For example, using the results of the above model, we estimate that, from month to month, Lender 1 has a 31 percent monthly cure rate, a 6 percent monthly default rate, and a 63 percent monthly "stays the same" rate, while Lender 7 has a 51 percent monthly cure rate, a 8 monthly percent default rate, and a 41 percent monthly "stays the same" rate.

Suppose both lenders have 100 delinquencies in month 2. By the end of the 3rd month, Lender 1 will have 31 cures, 6 defaults, and 63 delinquencies still at risk, while Lender 7 will have more cures (51), a few more defaults (8), and fewer loans remaining at risk (41), not taking into account any new delinquencies. In another month, Lender 1 will have another 19.5 cures (.31*63 loans remaining at risk in month 4), 3.8 defaults, and 39.7 loans still at risk, while Lender 7 will have 20.9 additional cures (20.9 = .51*41), 3.3 additional defaults (.5 less than Lender 1), and significantly fewer delinquent loans still at risk (16.8). In short, for every 100 delinquent loans over two months, despite its higher default rate, Lender 7 will experience just 1 to 2 more defaults than Lender 1 while curing 22 more delinquencies and leaving 23 fewer loans still at risk of default. These numbers will change over time.

Table 9 presents these predicted outcomes 6 months after a delinquency begins, the "6-month cumulative estimated hazard" for each lender, controlling for the other variables in the model and not layering in any new delinquencies. Within 6 months of a 30-day delinquency, 79 percent of Lender 1's delinquencies will have cured while 14.6 percent will have gone into default. In contrast, 85.5 percent of Lender 7's 30-day delinquencies will have cured and 14 percent will have ended up in default. So even though the monthly default rate of Lender 7 is higher than for Lender 1, the higher cure rate for Lender 7 results in more cures and slightly fewer defaults than for Lender 1 after 6 months. Moreover, over 6 percent of Lender 1's delinquencies will still be in a delinquent state 6 months after the delinquency began, compared to less than 1 percent for Lender 7.

In Table 9, we see that there appear to be roughly two groups of lenders when it comes to the 6-month outcomes of their delinquencies. Lenders 1, 5, and 6 all have 6-month cure rates of about 80 percent and 6-month default rates of about 15 percent or more. Lenders 2, 3, 4, and 7 along with the "other" lenders have 6-month cure rates around 85 percent and higher, and 6-month default rates around 14 percent and below. This latter group of lenders has slightly lower 6-month rates of still delinquent loans. Note, the group of "other" lenders performs best with the highest 6-month cure rate and lowest 6-month default rate.

From servicer to servicer, there are significant differences in the way systems, personnel, and processes are applied to non-performing loans between the 30th and 90th day of delinquency—the time period reflected by the above analysis. These differences may hint at why outcomes vary. Interviews conducted with several of Self-Help's major subservicers and discussions with Self-Help's Loss Mitigation and Servicing Manager highlight some of these differences. For example, one lender has one collector for every 15,000 loans it services and uses no risk-scoring system at all. This is in stark contrast with the three lenders who have at least one collector for every 5,000 loans and use either Risk Profiler (RP) or Early Indicator (EI) to prioritize their workloads (Russell 2005). Profiles of the different staffing, systems, and processes in use follow:

<u>Lenders 1, 5, and 6</u>:

Lender 1 is a small servicer, (fewer than 100,000 loans) and has one collections staff person for every 15,000 loans serviced and one loss mitigation counselor for every 45,000 loans. Staff does not specialize by investor or product type. They do not use a risk scoring system but they do use Fannie Mae's Home Saver Solution Network (HSSN) workout system.

Lender 5 is a large servicer (over 300,000 loans serviced). The ratio of loans serviced per collector falls between 5,000 and 10,000, while their ratio of loss mitigation specialists to loans is about one per 20,000. They use RP but no smart workout system.

Lender 6 was not interviewed.

<u>Lenders 2, 3, 4, and 7</u>

Lender 2 is a large servicer. It employs approximately one collections staff person per 10,000 loans and one loss mitigation specialist per 80,000 loans in its portfolio. Collectors do not specialize, while loss mitigation specialists do specialize by investor. Lender 2 uses both RP and EI in addition to HSSN for workouts.

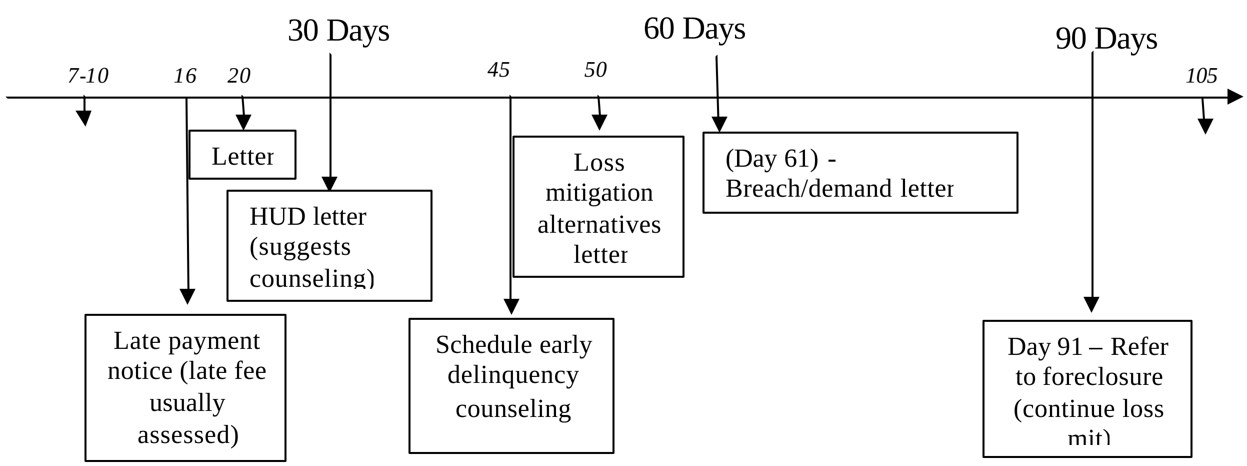
The main servicer for Lender 3 was not interviewed. Of interest is that a smaller, more recent servicer for Lender 3 was the only servicer who reported providing a (small) financial incentive to employees for completed workouts.

Lender 4 was not interviewed.

Lender 7 is a small servicer. While it staffs one collections person per 6,000 loans, the collectors specialize such that there is one collector assigned to the 2,000 affordable loans serviced. The loss mitigation employees—about one for every 20,000 loans in the portfolio—do not specialize. They use RP and Workout Profiler (Russell, 2005).

In the traditional process, the borrower must take some initiative to get into a loss mitigation plan, either by contacting the servicer or a housing counselor, or by filling out an information packet, which they receive by mail from the servicer. In August 2002, Self-Help began testing a more proactive approach. Self-Help engaged Balance, an affiliate of Consumer Credit Counseling of San Francisco, to proactively contact borrowers on the 45th day of delinquency. The program was activated with Lenders 1, 2, and 5 between 2002 and 2003, as well as others not profiled herein.[17]

Self-Help suggests that its subservicers follow a specific timeline through the delinquency process, but here again, servicers differ in their actual delinquency management process. It should be noted that Self-Help discourages the use of accelerated foreclosure timelines suggested by Fannie Mae for loans identified by Risk Profiler as high risk. Self-Help's servicing guidelines are as follows:



[17] Holder, Interview.

While servicers generally followed Self-Help's manual, there were some marked deviations. Lender 4 starts collection calls on day 1, and sends its loss mitigation alternatives letter very early—the 30th day—effectively encouraging workouts early in the delinquency timeline. Using a contrasting strategy, Lender 5 sends the breach letter on the 35th day, almost a month earlier than others and well in advance of a loss mitigation alternatives letter that is mailed 15 days later. Yet another, Lender 6, waits until the 90th day to send the breach letter. Lender 7 takes little action before the 60th day, when the HUD letter, loss mitigation letter, and breach letter are all sent within a few days of each other.[18] Whether one of these strategies is more effective or efficient cannot be determined from this analysis.

The Importance of Early Contact

The research literature suggests that most LMI borrowers will never miss a mortgage payment, that the majority of those who do will become current without any intervention by the servicer, and that this also holds for most loans that go into default, including higher risk government-backed mortgages. According to Collins, Belsky, and Tripathi (1999, 22), almost 60 percent of FHA defaults "are reinstated and become current without any intervention."

Nevertheless, academic and trade articles stress the importance of making early contact, as well as the difficulty in contacting late payers. For example, Countrywide Mortgage, the nation's biggest servicer, "relies largely on repeated phone calls and a barrage of mailings to reach—and reach out—to seriously delinquent borrowers" (Sichelman 2001, 18). According to Countrywide CEO Angelo Mozilo, "while written notification is a requirement, compassionate and understanding phone calls offering help should be the standard, best practice for loss mitigation…A variety of delinquency-scoring computer software systems are available to help

[18] Holder, interview.

servicers make this process cost-effective and manageable" (Mozilo 2000, 17). For a variety of reasons, however, "despite considerable effort, a servicer may never succeed in personally speaking with a good many borrowers prior to the commencement of foreclosure proceedings. When that happens, a borrower may have lost out on the counseling that could have worked out an alternative to foreclosure" (Trianna 1999, 11).

In December 2004, Freddie Mac began a pilot program dubbed the "affordable servicing initiative," in response to findings that servicers are often unable to make contact with up to half of all delinquent borrowers before foreclosure. The first phase of this initiative is aimed at helping servicers contact troubled borrowers that they have not been able to reach. Freddie Mac plans a second phase that will add "homeownership preservation to the affordable housing agenda" (National Mortgage News 2005a, 1).

While the authors of this article had no role in servicing CAP loans, we tried to use loan application and servicing records to contact borrowers to request their participation in our homebuyer panel. Our evaluation plan calls for an annual telephone interview of each panel member during the first five years of the member's loan term.

Although our original protocol called for us to obtain borrowers' telephone numbers from servicing records, only about a third of the telephone numbers from the 3,622 CAP borrowers' servicing records were current. Perhaps we were naïve to expect a higher hit rate, because loan applications are likely to contain phone numbers from borrowers' previous places of residence, which are sometimes in different states from where the borrower eventually bought a home. Widespread use of cell phones, for which there is yet no national telephone directory, unlisted numbers, and intermittent phone service (common for many with limited incomes), forced us to devote far more time and resources to contacting borrowers than we had originally bargained for.

Despite additional efforts, including directory assistance, on-line searches, and more costly third-party skip tracing vendors, we only marginally increased the number of accurate phone numbers, bringing our grand total to just 43 percent; at the end of the day, we were still left with incorrect telephone numbers for more than half of all attempted contacts.

Given our problems and Mozilo and other industry leaders' experiences in trying to reach out to delinquent borrowers, we decided to compare delinquency patterns for CAP borrowers that we successfully reached and those we could not find. For all 30-day delinquencies we analyzed the time until first 90-day delinquency from the date of our initial attempted contact, using a proportional hazards regression (see, e.g., Allison 1995):

$$\log h_i(t) = a(t) + b_1 X_{1i} + \ldots + + b_k X_{ki}$$

where $h_i(t)$ is the hazard for delinquency i at time t, X_{1i} through X_{ki} are a set of k independent variables. The model is estimated using a partial likelihood estimator.

A univariate analysis of the worst delinquency experience for CAP borrowers we were able to reach (Contact) and those for whom no working phone number was found (No Contact) shows no significant differences from the overall rates presented earlier (see Table 10). Average FICO scores and missing credit scores are about the same, as are delinquency experiences. Between 80 percent and 82 percent of both groups were never delinquent, while around 5.5 percent of both groups defaulted at least once.

However, when we specified a proportional hazards regression model using time until first 90-day delinquency as the dependent variable, controlling for credit score, we find that the No Contact borrowers reach this default threshold around 27 percent faster than those for whom we were able to secure accurate telephone numbers, and this result is (borderline) statistically significant at the .10 level (Table 11).

When we model the outcomes of 30-day delinquencies, the results are even more robust. Controlling for specified loan and borrower characteristics, No Contact delinquent borrowers were 21 percent less likely to cure than those for whom we had correct telephone numbers, but they were just as likely to default (see Table 12). Controlling for specified loan and borrower characteristics, the monthly cure rate for No Contact delinquent borrowers was 21 percent less than the rate for those we were able to reach, but there was no significant difference in monthly default rates (Table 13).

Finally, when we estimate 6-month cumulative probabilities, the lower cure rates for No Contact delinquent borrowers turn into higher cumulative default rates, similar to the earlier analysis by lender. Again, this is because lower cure rates mean delinquent borrowers remain at risk of going 90 days for longer periods, so even though monthly default rates don't differ, the cumulative default rates for No Contact late payers is greater (Table 14). Controlling for loan and borrower characteristics, 21 percent of delinquent No Contact borrowers will default over a 6-month period, compared with 19.5 percent of delinquent borrowers whom we were able to contact. Although not all defaults turn into foreclosures, the 6-month differences in cumulative default rates can translate into greater servicing and investor costs.

Conclusions

The unprecedented growth in homeownership among lower and moderate income families during the 1990s raised the importance of the back end of the home buying transaction—loan servicing and post-purchase default management. Although delinquency and default rates increased as the economy fell into recession, it is possible that many more financially squeezed homeowners would have lost their homes had it not been for the innovations in loan servicing discussed in this paper. At this writing, the looming possibility of softening housing markets suggests that these tools may become even more important in the near future. The proliferation of affordable mortgage products featuring more flexible underwriting standards and the fact that LMI families, immigrants, and minorities will account for an increasing share of the first-time home buying market for the foreseeable future suggest that the economic fortunes of mortgage institutions will be increasingly tied to the effectiveness of their loan servicing operations.

Although it may not be possible to generalize for all affordable lending programs, early findings from our evaluation of the Community Advantage Secondary Market Demonstration Program are nevertheless suggestive. A significant share of CAP borrowers and co-borrowers who bought their homes prior to the onset of the 2000–01 recession have experienced multiple spells of joblessness and missed housing payments since they closed their loans. Yet the vast majority of CAP borrowers have never missed a payment, and a small fraction account for a disproportionately large share of total delinquency spells, as well as defaults. In fact, compared to industry benchmarks, CAP loans perform quite well. With less than 1 percent of all CAP loans having been foreclosed, and a loss severity rate of just 26 percent of original loan balance, Self-Help's loss mitigation efforts are quite effective.

Against this overall backdrop, we find that even after controlling for loan and borrower characteristics, and regional economic conditions, the pattern of delinquency outcomes—whether a late-paying borrower catches up on her payments, sinks further into delinquency,0 or defaults—differ significantly across participating lenders, which suggests that servicing strategies do matter.

In addition, while research confirms the importance of early contact with delinquent borrowers in effective default management, we found high rates of incorrect telephone numbers on loan application and servicing records, with those homebuyers we had difficulty reaching demonstrating poorer payment records than others.

In closing, we should also note that, as suggested by industry data as well as our own interviews, default management costs drive servicing profits, and loan servicing remains a labor-intensive process, smart technologies not withstanding. As one CAP servicer put it: If I had to choose between the best technology or the best people, I would take the people. Great people can make good technology work even better.

Finally, with the rate of appreciation for housing prices slowing, the range of cost-effective workout options that would enable defaulted borrowers to remain in their homes may be narrowing, so that it becomes even more important to diffuse smart servicing technologies as widely as possible among affordable housing lenders and servicers. With the systems now available, foundation and government grants for access and training could accelerate the rate at which these smart servicing systems are adopted by smaller affordable lenders and nonprofit financial counseling agencies. And this, in turn, could make their preventive servicing efforts smarter and more cost-effective.

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Table 1
Community Advantage Loans
Descriptive Statistics for Loans Purchased before January 1, 2003

Number of Loans: 28,131		
Variable	Percent	Median
Credit Score		
No Credit Score	15.3%	
FICO <= 620	14.4%	
FICO 621-660	18.3%	
FICO 661-720	26.2%	
FICO >720	25.7%	
Loan Characteristics		
LTV		97.0%
Backend Ratio		36.1%
Age of Loan at Purchase (months)		11
Borrower Characteristics		
Female Borrower	44.1%	
African-American Borrower	21.2%	
Hispanic Borrower	16.6%	
Single Parent*	15.9%	
First-Time Homebuyer	45.7%	
Income at Origination		$29,532
Income as % of AMI[†]		59.6%
Post-Purchase Employment History*		
Current Unemployment (Borrower)	3.1%	
Current Unemployment (Spouse)	8.3%	
Currently >1 Job (Borrower)	16.1%	
Currently >1 Job (Spouse)	10.4%	
Any Unemployment since Purchase (Borrower)	16.8%	
Any Unemployment since Purchase (Spouse)	59.3%	
Currently Work Full-Time (Borrower)	95.9%	
Currently Work >50 Hours per Week (Borrower)	27.8%	
Two-Wage Earner Households (among Married/Partnered Households)	75.9%	
Geography		
Rural	19.2%	
North Carolina Borrower	40.1%	
California Borrower	12.9%	
Oklahoma Borrower	7.0%	
South Carolina Borrower	6.0%	
Ohio Borrower	4.3%	
Virginia Borrower	3.9%	
Georgia Borrower	2.7%	
Texas Borrower	2.6%	
Florida Borrower	2.5%	
Illinois Borrower	2.3%	
Other States	15.6%	

Source: Self-Help Community Advantage, Community Advantage Panel Survey, and authors' calculations.
* This estimate is based on data collected as part of the baseline survey of the Community Advantage Panel Survey, a 5-year study of over 3,500 CAP borrowers.
[†] AMI is Area Median Income, i.e. median income of the MSA or State for non-MSA areas

Table 2
Worst Delinquencies

	Number of Loans	Percent
Never 30-days Delinquent	22,162	78.8
Never Worse than 30/60 Days	4,099	14.6
90 Days Delinquent	1,870	6.7
Total	**28,131**	**100**

Source: Self-Help Community Advantage and authors' calculations
Note: Percentages may not sum to 100 due to rounding

Table 3
Number of 30-Day Delinquencies

	Number of Loans	Percent	Average Length of Delinquency
Never Delinquent	**22,162**	**78.8%**	
Ever Delinquent	**5,969**	**22.2%**	**2.55 months**
Only One Delinquency	*2,564*	*9.1%*	2.50 months
Two Delinquencies	*1,246*	*4.4%*	2.66 months
Three Delinquencies	*756*	*2.7%*	2.57 months
Four Delinquencies	*477*	*1.7%*	2.73 months
Five or More Delinquencies	*926*	*3.3%*	2.46 months
Total	**28,131**	**100%**	

Source: Self-Help Community Advantage and authors' calculations
Note: Percentages may not sum to 100 due to rounding

Table 4
Percentage of 30-day Delinquencies that end in Default
By Delinquency Order

	Number of Spells	Number of Defaults	Percent
First Delinquency	5,969	786	13.2
Second Delinquency	3,405	520	15.3
Third Delinquency	2,159	319	14.8
Fourth Delinquency	1,403	236	16.8
Fifth or Higher Delinquency	2,500	339	13.6
Total	**15,436**	**2,200**	**14.3**

Source: Self-Help Community Advantage and authors' calculations
Note: Percentages may not sum to 100 due to rounding

Table 5
Outcomes of 30-day Delinquencies

Outcome	# of Delinquency Spells	Average Duration (months)
Cured	12,838 (83.2%)	2.1 months
Went 90-days Delinquent	2,200 (14.3%)	4.1 months
Still 30/60-days Delinquent	398 (2.6%)	7.2 months
Total	**15,436 (100%)**	**2.6 months**

Source: Self-Help Community Advantage and authors' calculations
Note: Status as of December, 2002 for all delinquencies beginning prior to July, 2002. Delinquencies that ended in a prepayment prior to going 90-days were coded as "cured".
Percentages may not sum to 100 due to rounding

Table 6
Outcomes of 30-day Delinquencies
By Lender[†]

Lender	% Cured	% 90-days delinquent	% 30-60 days delinquent
Lender 1	76.5%	20.1%	3.4%
Lender 2	84.6%	13.0%	2.5%
Lender 3	86.2%	12.2%	1.6%
Lender 4	87.4%	10.6%	2.0%
Lender 5	75.6%	21.5%	2.9%
Lender 6	77.2%	19.7%	3.1%
Lender 7	81.0%	15.5%	3.5%
All Others	86.3%	10.8%	2.9%
Total	**83.2%**	**14.3%**	**2.6%**

Source: Self-Help Community Advantage and authors' calculations
Note: Status as of July 2003 for all delinquencies occurring prior to January 2003.
Percentages may not sum to 100 due to rounding
[†]Lenders were chosen for inclusion in our analysis based on having 600 or more delinquencies.

Table 7
Outcomes of 30-Day Delinquencies
Hazard Regression Results
Trimmed Model
Probability of Curing

Variable	Coefficient	Standard Error	Odds Ratio
Constant	.244	.186	--
No FICO	-.089	.147	.91
FICO < 620	-.051	.138	.95
FICO 620-659	-.052	.140	.95
FICO 660-719	.138	.145	1.15
LTV >= 95	-.066	.064	.94
Female Borrower	.184**	.055	1.20
African-American Borrower	-.324**	.061	.72
Hispanic	.117	.107	1.12
Income as % of AMI†	.001	.001	1.00
Age of Loan (months)	.002	.001	1.00
# of Previous Delinquencies	-.096**	.014	.91
North Carolina Borrower	-.199*	.090	.82
California Borrower	-.073	.138	.93
Lender 1	-.663**	.114	.51
Lender 2	-.022	.094	.98
Lender 3	.372**	.114	1.45
Lender 4	-.027	.103	.97
Lender 5	-.329**	.108	.72
Lender 6	-.305*	.147	.74
Lender 7	.163	.128	1.18

Source: Self-Help Community Advantage and authors' calculations.
Note: The full model included the following insignificant variables: No Credit Score, FICO 621-660, FICO 661-720, High Backend Ratio, Hispanic Borrower, First-Time Homebuyer, and additional state dummies
† AMI is Area Median Income, i.e. median income of the MSA or State for non-MSA areas
* -- p<=.05; ** -- p<=.01

Table 8
Outcomes of 30-Day Delinquencies
Hazard Regression Results
Trimmed Model
Probability of Going 90-days Delinquent

Variable	Coefficient	Standard Error	Odds Ratio
Constant	-1.390**	.219	--
Missing FICO	.171	.168	1.19
FICO <= 620	-.013	.161	.99
FICO 620-659	-.108	.164	.90
FICO 660-719	.107	.168	1.11
LTV >= 95	.028	.078	1.03
Female Borrower	.061	.064	1.06
African-American Borrower	-.373**	.072	.69
Hispanic	-.291*	.136	.75
Income as % of AMI†	-.005**	.002	.99
Age of Loan (months)	-.003	.002	1.00
# of Previous Delinquencies	-.062**	.016	.94
North Carolina Borrower	-.188	.104	.83
California Borrower	-.248	.187	.78
Lender 1	-.015	.133	1.01
Lender 2	.232*	.115	1.26
Lender 3	.521**	.137	1.68
Lender 4	.007	.128	1.01
Lender 5	.307*	.125	1.36
Lender 6	.314*	.153	1.37
Lender 7	.415**	.149	1.51
Model Fit			
Wald χ^2	454.33**		
Df	40		

Source: Self-Help Community Advantage and authors' calculations.
Note: The full model included the following insignificant variables: No Credit Score, FICO 621-660, FICO 661-720, High Backend Ratio, Hispanic Borrower, First-Time Homebuyer, and additional state dummies
† AMI is Area Median Income, i.e. median income of the MSA or State for non-MSA areas
* -- p<=.05; ** -- p<=.01

Table 9
Predicted Outcomes of a Typical 30-day Delinquency
Within 6 Months, by Lender†
(6-month Cumulative Estimated Hazard Based on Survival Regression Model)

Lender	% Cured	% 90-days delinquent	% 30-60 days delinquent
Lender 1	79.0%	14.6%	6.4%
Lender 2	85.9%	13.1%	1.1%
Lender 3	85.8%	14.1%	0.2%
Lender 4	87.8%	10.9%	1.3%
Lender 5	81.6%	15.9%	2.4%
Lender 6	81.9%	15.8%	2.3%
Lender 7	85.5%	14.0%	0.5%
Others	88.1%	10.7%	1.2%

Source: Self-Help Community Advantage and authors' calculations
Note: Predicted probabilities control for the additional borrower and loan characteristics included in the model.
†Lenders were chosen for inclusion in our analysis based on having 600 or more delinquencies.

Table 10
Worst delinquency and Contact/No Contact
Since Attempted Contact

Contact	Never Delinquent		30-days Delinquent		60-days Delinquent		90+-days Delinquent		Total		Mean Credit Score	Credit Score Missing
	#	%	#	%	#	%	#	%	#	%		
No	1627	79.5%	218	10.7%	84	4.1%	117	5.7%	2046	100	644	12.3%
Yes	1284	81.8%	160	10.2%	42	2.7%	84	5.4%	1570	100	642	10.7%

Source: Self-Help Community Advantage and authors' calculations.
Note: Percentages are row percentages. May not add to 100 due to rounding.
The association between contact and delinquency is not significant.

Table 11
Time Until First 90-Day Delinquency Since Attempted Contact
Proportional Hazards Regression

Variables	Hazard Ratio
No Contact	1.273*
FICO 620 or Lower	6.805**
FICO 621-660	3.503**
FICO 661-720	1.454
FICO missing	4.504**
No FICO Score	2.987*
N	3,240
X^2	86.3**
Df	6

Source: Self-Help Community Advantage and authors' calculations.
*   - p<.10
** - p<.01

Table 12
Outcomes of 30-day Delinquencies
Survival Regression Results, Trimmed Model
(N=1,059 30-day delinquency spells)
Probability of Curing

Variable	Odds Ratio
No Contact	.79*
FICO missing	.56**
FICO <= 620	.77
FICO 621-660	.77
LTV>=95	.67*
African-American Borrower	.83
Hispanic borrower	1.38
Age of Loan (months)	1.04

Source: Self-Help Community Advantage and authors' calculations.
Note: The full model included the following insignificant variables: No Credit Score, FICO 661-720, High Backend Ratio, Female Borrower, First-Time Homebuyer
* -- p<=.05; ** -- p<=.01

Table 13
Outcomes of 30-day Delinquencies
Survival Regression Results, Trimmed Model
(N=1,059 30-day delinquency spells)
Probability of Going 90 Days Delinquent

Variable	Odds Ratio
No Contact	.99
FICO missing	1.01
FICO <= 620	1.19
FICO 621-660	.78
LTV>=95	.71
African-American Borrower	1.05
Hispanic borrower	1.26
Age of Loan (months)	1.03
Model Fit	
Wald χ^2	37.98**
Df	7

Source: Self-Help Community Advantage and authors' calculations.
Note: The full model included the following insignificant variables: No Credit Score, FICO 661-720, High Backend Ratio, Female Borrower, First-Time Homebuyer
* -- p<=.05; ** -- p<=.01

Table 14
Predicted Outcomes of a Typical 30-day Delinquency
Within 6 Months
By Contact Status
(6-month Cumulative Estimated Hazard Based on Survival Regression Model)

Contact	% Cured	% 90-days delinquent	% 30-60 days delinquent
No	70.4%	19.9%	9.7%
Yes	75.4%	18.3%	6.3%

Source: Self-Help Community Advantage and authors' calculations