Preventive Servicing Is Good for Business *and* Affordable Homeownership Policy

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Abstract

This article 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. We suggest that the loan servicing side of the affordable housing delivery system may be underappreciated and undercapitalized.

We use a database of more than 28,000 affordable housing loans to test several preventive servicing–related propositions and find that after we control for loan and borrower characteristics, the likelihood that a delinquent mortgagor within this universe will ultimately default varies significantly across servicers. This suggests that loan servicing is an important factor in determining whether low- and moderate-income borrowers who fall behind in their mortgage payments will end up losing their homes through foreclosure. It also suggests a need for policy makers to incorporate preventive servicing into affordable homeownership programs.

Keywords: Affordability; Defaults; Mortgage servicing

Introduction

Favorable demographics, unparalleled economic growth, and low interest rates combined with an aggressively supportive public policy propelled homeownership rates upward during the 1990s to a 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, 1). Home Mortgage Disclosure Act records verify an impressive increase in mortgages to low- and moderate-income families—38 percent between 1993 and 1997, compared with an increase of 27 percent for loans to higher-income households (Quercia, McCarthy, and Wachter 2003). This growth in mortgages to low- and moderate-income 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 "job-loss" recovery, the number of financially stressed families grew, and the number of homeowners spending 50 percent or more of their income for mortgage, insurance, and utilities increased by 1.2 million (78 percent) between 1997 and 2003 (Lipman 2005). Such high housing costs inevitably lead to more volatile payment patterns for low- and moderate-income homeowners, whose higher level of debt to income makes them more sensitive than homeowners in general to even modest declines in the demand for labor. This partly explains why default rates for more flexibly underwritten, higher loan-to-value ratio (LTV) government-backed loans tend to be significantly higher than they are for conventional mortgages as a whole.[1] A review of the literature on the well-established relationship between LTVs and propensity to default found that "default depends clearly on loan characteristics, mainly home equity" (Quercia and Stegman 1992, 376).

Efforts to increase the homeownership rate by increasing the number of new mortgagors can be successful only to the extent that these new homeowners can maintain their tenure. According to a recent U.S. Department of Housing and Urban Development (HUD) study, "[P]olicies 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" (2004, v).

If the 1990s were 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, 4). These services include collections and default management

[1]For example, from 1993 to 2000, the rate of foreclosures for Federal Housing Administration (FHA) loans was at least twice that of conventional loans and the 90-day past-due rate was three to six times higher for FHA loans than for conventional ones (HUD 2003).

strategies designed to keep delinquent homeowners from losing their homes through foreclosure. This article 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, we will review the economics of the loan servicing business. Then, using a database of more than 28,000 affordable home loans that we are collecting as part of a multiyear evaluation of a secondary mortgage market demonstration undertaken by Self-Help, a leading community development financial institution, we empirically test several servicing-related propositions:

1. That affordable mortgages can have a high likelihood of recovery from early-stage delinquency
2. That certain borrower, loan, property, and payment history attributes affect cure rates (cure means that the borrower makes up the missed payments)
3. That loan servicing plays a role in determining the ultimate outcome of delinquency spells

Preventive and smart servicing

In this article, 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).[2] "Smart servicing tools" 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 nonperforming 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 at which time, and success in avoiding foreclosure often depends on early intervention. For example, in a 2001 review of Federal Housing Administration (FHA) loans, one servicer had a success rate that exceeded 45 percent for workouts processed within the first two months of delinquency, but only a 10 percent success rate if the workout was processed

[2] For a full discussion of alternatives to foreclosure, see Cutts and Green (2005).

after seven months (HUD 2002). Deloitte, the consulting firm, estimates that organizations that adopt what it refers to as predictive analytics and other preventive servicing practices “can enjoy substantial benefits including a 20 percent improvement in the dollars collected, reductions of up to 30 percent in overall operating costs, and declines of up to 20 percent in roll rates (or accounts rolling to the next stage of delinquency)” (Caldwell and Jordan 2006, 2). However, engaging a delinquent mortgagor quickly is sometimes easier said than done. As a case in point, when Countrywide Mortgage tried to help 300 seriously delinquent Chicago-area homeowners avoid foreclosure, only 38 responded (Sichelman 2001). Frustrated by such low response rates, the company sent a “team of loss mitigation specialists” 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.

Affordable mortgages, smart servicing, and mortgage economics

Lending programs designed to increase the homeownership rate for low- and moderate-income borrowers through liberalized underwriting guidelines also increase the likelihood that those homeowners will default. Beginning in the late 1980s and continuing through the 1990s, lenders, mortgage insurers, and secondary marketing agencies responded to policy goals and regulatory pressures by relaxing the guidelines that sometimes barred lower-income households from qualifying for a mortgage. These guidelines evolved to minimize the required down payment, reduce the borrower’s asset and contribution requirements, raise the allowable monthly debt payments at particular income levels, and loosen creditworthiness standards. While these features allow more households to buy homes, they can increase the risk of delinquency and default by 40 to 400 percent (Steinbach 1995). Because of the increased incidence of default and because low- and moderate-income borrowers typically have little financial cushion to fall back on in the event of an economic setback (Baku and Smith 1998), calls to “implement homebuyer support structures designed to ensure long-term homeownership” point the way to preventive servicing measures for these homeowners (Steinbach 1995, 39).

The smart servicing tools now in use can be particularly effective for these borrowers. The combination of early intervention, the targeting of borrowers most at risk of default, and workout options that allow borrowers to recover from financial setbacks all help servicers focus resources on those loans that can benefit the most from intervention. In effect, flexible guidelines and preventive servicing have the same ultimate aim: to bolster the ranks of homeowners.

Because of the high cost of defaults, smart and preventive servicing generally makes good business sense for any mortgage. For example, the FHA-expected loss per defaulted loan ranges from 30 percent to 40 percent of the loan amount,[3] thus suggesting that avoiding foreclosure can save as much as $60,000 to $80,000 on the maximum FHA loan in standard-cost areas. Though most conventional or affordable mortgage defaults do not end in foreclosure, those that do can be quite costly. For example, Cutts and Green cite Focardi's findings 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 (2005, 352).

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 cost of more than two additional workouts (cited in Capone and Metz 2003, 10). Since affordable housing mortgages with their typically smaller equity cushions are more likely to default[4] and to 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 largely borne 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, investors and insurers must look to that entity to implement these loss-minimizing practices, which are often labor intensive or require investments in new technologies and training—or both.

[3]For example, the 2005 analysis of FHA's Mutual Mortgage Insurance Fund indicates that the average loss severity rate experienced by FHA from 2000 to 2004 ranged from 30.59 percent on streamlined refinance adjustable-rate mortgages to 48.76 percent on 15-year non-streamlined refinance fixed-rate mortgages. From 2002 to 2003, the average loss rate per claim was 35 percent (HUD 2005).

[4]For example, a mortgage insurance company found that loans with down payments of 3 percent of the borrower's own funds had twice the default rate of loans with a 5 percent down payment (Steinbach 1995).

Servicer economics relies on maximizing efficiency, with consolidation driven by technology and economies of scale. Between 1989 and 2005, the share of the market held by the 5 largest servicers went from 7 percent to 42 percent, with the 25 largest holding 69 percent of the market (Inside Mortgage Finance 2006). In the drive to take advantage of 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 10 years. Direct servicing costs per loan per year, which were $80 to $90 in the late 1980s, were shaved to less than $50 in 2000 (Oliver et al. 2001).

On the revenue side of the equation, the largest single source of revenue is servicing fees. The standard fee for conventional conforming home loans is one quarter of 1 percent (25 basis points) of the outstanding balance of the loan annually. On government-backed loans, the fee is generally 44 basis points annually (Muolo 2000), a reflection of lower average loan balance, more reporting requirements, and higher costs associated with servicing FHA and U.S. Department of Veterans Affairs (VA) loans.

Some previous research indicates that servicing methods can make a difference in outcomes for subprime borrowers. A large servicer examined 23,000 delinquency transitions over nearly four years—from current to delinquent, from delinquent to foreclosure or to cure, and from foreclosure to cure—in subprime loans from several different servicers (Sjaastad et al. 2005). The analysis validates the predictiveness of such factors as current FICO (Fair, Isaac & Company) score, LTV, loan age, and payment history for each transition type, yet after controlling for these factors, the authors conclude that "servicers can have specific, strong impacts on transition rates and delinquency duration times" in subprime mortgages (Sjaastad et al. 2005, 16). This servicer effect seems reasonable, for once a loan is closed, the servicer has an ongoing relationship with the borrower and is in a position to influence outcomes.

To illustrate, when a loan reaches 60 or 90 days delinquent, one servicer promptly refers the loan to a foreclosure attorney, as state law allows, and insists that the borrower pay full arrearages and fees to halt foreclosure, something a financially troubled borrower usually cannot do. Another servicer contacts the borrower, exercises forbearance, accepts partial payments, and actively helps formulate an alternative to foreclosure. In the first case, the delinquent loan quickly transitions to foreclosure, while in the second, the borrower remains in the early-delinquency stage until either catching up or defaulting several months later. Delinquent loan servicing practices are differentiated by such factors as allocation of resources (both staff and technology), the process in place for nonperforming loans, investor preference, and organizational commitment to loss mitigation, many of which are considered in this article.

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 from the research and our examination of the Self-Help portfolio of the special challenges posed by this market segment.

Over 30 years ago, the relationship between average loan size and discounted, net servicing revenue was found to be positive and nonlinear (McConnell 1976). In 2001, the average conventional mortgage loan balance was $120,393 (HMDA 2001). The average loan balance in Self-Help's program is substantially lower: $79,800. Thus, the annual servicing fees generated on the average Self-Help loan are 34 percent lower than the fees for the average conventional loan ($200 versus $301). However, late fees generated by the increased incidence of delinquency may offset this differential somewhat.[5] More recently, Linda Simmons, a Stratmor Group partner, analyzed a large pool of mortgage data from 1999 to 2002 and found "a strong relationship between portfolio composition and servicing costs" (DeZube 2003, 48). The Stratmor Group found that 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" (DeZube 2003, 48). Borrowers who have 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, affordable mortgages may exhibit slower and less volatile prepayment patterns. In their analysis of the 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 to prepay than borrowers with better credit. By tracking Freddie Mac loans purchased from 1993 to 1997 through the end of 1999, Van Order and Zorn (2004) found that low-income and minority borrowers prepay mortgage loans less rapidly when conditions are favorable for refinancing. If indeed low- and moderate-income mortgages prepay more slowly than other types of conventional mortgages, their servicing revenue stream will be longer and potentially more valuable.

[5] Late fees, incurred for payments received after the 15th of the month, are typically 3 percent to 5 percent of the payment (sources include CaliforniaRealEstateCenter.com 2006 and MortgageNewsDaily.com 2005).

To summarize, the business challenges in servicing mortgages originated largely for Community Reinvestment Act (CRA) credit are compounded by their smaller size and higher delinquency and default rates. Although these challenges may be offset to some extent by slower prepayment patterns, we argue that the mortgage servicing industry needs to implement the most efficient default management systems possible to keep costs down while still meeting investor requirements to minimize losses. We believe that consistent with the public policy goal of sustaining homeownership, investor/insurer and servicer goals might be aligned in the development of smart servicing tools.

The evolution of smart servicing tools[6]

Advanced information technologies were first applied to collection management in the credit card industry during the early 1990s as the percentage of those making minimum or no monthly payments swelled along with aggregate debt levels. This sector was a fertile testing ground for decisioning systems that analyze the behavior patterns of delinquent cardholders and determine who is least likely to pay without early intervention (Waggoner 2002).

In a parallel fashion, first-generation automated mortgage servicing models, introduced in the mid-1990s, identify delinquent mortgage accounts that are likely to benefit most from early intervention. These tools, such as Freddie Mac's EarlyIndicator℠ (EI) and Fannie Mae's Risk Profiler® (RP), use a combination of borrower information contained in the mortgage application, loan-specific payment patterns, and updated credit information on the borrower (Fannie Mae 2005a; Freddie Mac n.d.). Personal contact with the 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 servicing systems.

The second phase 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 GE's mortgage insurance company's Loss Mitigation Optimizer, Freddie Mac's Workout Prospector®, and Fannie Mae's Workout Profiler™ to assess the viability of foreclosure alternatives in each case. These tools essentially apply consistent underwriting methodology to keep borrowers in their homes by assessing what one industry expert refers to as the "three Cs"—capacity, collateral, and commitment (Kehr 2005).

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

Because investors and insurers stand to gain the most from aggressive loss mitigation, they often served as catalysts for the initial introduction of utilities and technology in this area and invested heavily in them. Today, such tools are increasingly being developed or enhanced by third-party software companies and are being integrated more directly into the servicers' systems (Kehr 2005). While many of these tools go hand in hand, they can be used independently and with mortgages of many different types.

Having launched its own loss mitigation program in 1996, FHA is committed to preventive servicing as well. By 2005, FHA officials affirmed their belief that the loss mitigation program "is becoming the dominant approach to address a default" ("FHA Cites 90,000 Loss Mit Cases" 2005, 91). 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, with FHA avoiding an estimated $2 billion in losses ("FHA Cites 90,000 Loss Mit Cases" 2005).

Instead of developing its own tools, FHA relies on servicers to apply commercially available smart servicing tools to its loans. It also instituted a system of scoring servicers and awards financial incentives—$27 million in 2005—for outstanding loss mitigation performance ("FHA Cites 90,000 Loss Mit Cases" 2005. FHA is not the only investor to score or pay servicers for using alternatives to foreclosure. Freddie Mac's Servicer Performance Profiles use such indicators as cure rates, workouts, and timeliness of foreclosure to benchmark servicers (Melchiorre 1999). One servicer reported earning $25,000 per month from 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 2002, 3).

Evidently, smart and preventive servicing has been financially effective for investors and insurers and even for servicers. But how effective has it 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 2004 alone; according to Kehr (2005), more than 92 percent received workouts that allowed them to stay in their homes.[7] The success of loss mitigation efforts is often gauged by the workout ratio, which generally

[7]Not all workouts result in retaining the home; other strategies used to avoid foreclosure involve the borrower's giving up or selling the home voluntarily, such as in the case of deeds-in-lieu and preforeclosure sales (Cornwell 2003).

compares the number of loans that receive successful workouts with the total number of loans that either get workouts or become real estate owned (when the title is transferred to the lender through foreclosure or in lieu of foreclosure). Details of this measure can vary; for example, Freddie Mac excludes repayment plans in tallying workouts, but Fannie Mae includes them.

From 1996 to 2000, Fannie Mae's workout ratio rose from 32 percent to 53 percent, while Freddie Mac's rose from 26 percent to 38 percent (Cordell 2001; Cornwell 2003). FHA's workout ratio nearly doubled from less than 15 percent in late 1997 to almost 30 percent at the end of 1999 (Herbert, Gruenstein, and Burnett 2000) and over 50 percent by 2002 (Cutts and Green 2005). Most strikingly, the number of FHA problem loans that were resolved using a home retention workout increased some 88 times, from 770 in 1997 to 68,003 in 2003. After introducing its Loss Mitigation Optimizer, GE's mortgage insurance company reported almost doubling its cure ratio —the share of all loans for which the company receives notification of delinquency but that later become current (Venetis 2001).[8] After implementing a collection scoring tool, one servicer reported a 50 percent increase in FHA and VA workouts (Abraham 1999); another claims that workouts tripled in the initial period after a "BackInTheBlack" loss mitigation system was implemented (O'Connor 2003). From 2000 to 2004, 145,000 Freddie Mac borrowers, or "130 families every business day," were kept in their homes with loan modifications, repayment plans, and forbearance ("Now, 'Affordable Servicing'" 2005, 1).

Perhaps the clearest evidence comes from Cutts and Green's 2005 examination of Freddie Mac–owned loans that went from 60 to 120 days delinquent between January and September 2001. Following these loans for 18 months, Cutts and Green found that using a repayment plan lowered the probability of failure by 80 percent for borrowers with higher incomes and by 68 percent for low- and moderate-income borrowers.

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

Servicing issues and Self-Help data

In this section, we use a unique data set of more than 28,000 mortgages made to low- and moderate-income borrowers to explore the impact of vari-

[8]Notification typically comes at 90 days, however, it could be sooner, for example, in the case of monthly pay policies.

ous factors on delinquency transitions (from delinquent to seriously delinquent or to cure) and to isolate the effects of servicing.

The Self-Help secondary market demonstration program is a multibillion-dollar initiative designed to expand homeownership opportunities for creditworthy, low-income, low-wealth individuals who are not effectively served by the conventional market. The program is a partnership among the Ford Foundation; the Center for Community Self-Help, a North Carolina-based community development organization; and Fannie Mae, a secondary market entity. The goal of the program is to provide tangible evidence that low-wealth borrowers are "bankable" and that secondary market actors can significantly expand their purchase of affordable housing loans without compromising either their balance sheet or their safety and soundness.

With a Ford Foundation grant to underwrite a significant portion of the credit risk, Self-Help purchases affordable mortgages (CRA loans) that could not otherwise be readily sold in the secondary market because of their perceived higher risk. Self-Help then sells the loans to Fannie Mae while retaining full recourse, meaning that Self-Help is obliged to cover any losses Fannie Mae may incur as a result of defaults. Self-Help contracts with participating mortgage lenders to originate and subservice the loans.

Self-Help mortgage products feature flexible underwriting and typically include one or more of the following features: a low down payment or none at all, 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 that were made to low- and moderate-income mortgagors and purchased by Self-Help before January 1, 2003; the average original balance was $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 of purchase by Self-Help.[9] The database is being compiled as part of our ongoing multiyear evaluation of Self-Help's program with the aim of

1. Measuring loan performance by tracking delinquency, default, and foreclosure rates over the critical first five years of the mortgage term

[9] A small number of months are missing from the payment history file. We have data on 580,276 loan-months, with 532 loan-months missing. We use an algorithm to fill in the likely values for the missing months. For example, if month 1 was paid on time and month 3 was paid on time, we assume that month 2 was also paid on time. Similarly, if month 1 was paid on time but month 3 shows a 60-day delinquency, we assume that 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.

2. Documenting the social and economic impacts of homeownership on borrowers
3. Assessing to the extent practicable the impacts of the program on neighborhood conditions and housing market dynamics

As part of the evaluation, we are building a panel of over 2,700 homeowners (as of 2005) who are being interviewed in six annual waves running through 2008. Some of the descriptive data cited later in the article are from our baseline phone interviews, which were conducted between late 2001 and 2003. This baseline survey gathered information on the home purchase and mortgage process, along with demographic and economic data. Core questions are repeated every year, while different modules (social capital, wealth and assets, financial behaviors and attitudes, sense of community, and mover survey) are used in different years.

Who are these homeowners?

Demographic and other characteristics of the borrowers

Almost 40 percent of Self-Help borrowers are minorities and 44 percent are women. An estimated 16 percent are single parents.[10] It is important to note that half had incomes below 60 percent of the local median household income when they closed on their loans (table 1). Moreover, a little over 40 percent of all Self-Help 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, Self-Help homeowners are about twice as likely to be minorities, almost five times as likely to have incomes below 60 percent of the area median income, as defined by HUD, and two and a half times as likely to be female (Center for Community Self-Help n.d.).

Data from our baseline survey of 3,727 Self-Help homeowners, which occurred generally around 12 to 24 months after home purchase, allow us to look at the family and employment situations of these borrowers in greater detail. As a rule, Self-Help families have a strong commitment to the work force; more than three-quarters of all sampled households with married couples or partners have two wage earners. Moreover, 16 percent of all borrowers and 10 percent of all spouses or partners who work have more than one job, including part-time, weekend, and evening work, and 96 percent of our surveyed borrowers work at least full-time (35 or more hours per week). Almost 30 percent average at least 50 hours of paid work per week.

[10]This figure is an estimate for the entire population of Self-Help borrowers based on the baseline panel survey.

Table 1. Self-Help Loans: Descriptive Statistics for Loans Purchased before January 1, 2003 (N = 28,131)

Variable	Percentage	Median
Credit score		
No credit score	3.5	
FICO 620 or lower	17.2	
FICO 621 to 660	21.0	
FICO 661 to 720	30.4	
FICO above 720	28.0	
Loan characteristics		
LTV (%)		97.0
Back-end ratio (%)		36.7
Age of loan at purchase (months)		11
Borrower characteristics		
Female borrower	44.0	
Black borrower	21.3	
Hispanic borrower	16.6	
Single parent[a]	15.9	
First-time home buyer	43.8	
Income at origination		$29,472
Income as a percentage of AMI		59.7
Postpurchase employment history[a]		
Current unemployment (borrower)	3.1	
Current unemployment (spouse)	8.3	
Currently more than one job (borrower)	16.1	
Currently more than one job (spouse)	10.4	
Any unemployment since purchase (borrower)	16.8	
Any unemployment since purchase (spouse)	59.3	
Currently works full-time (borrower)	95.9	
Currently works more than 50 hours per week (borrower)	27.8	
Two-wage-earner households (among married/partnered households)	75.9	
Geography		
Rural	20.5	
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 database, panel survey, and authors' calculations.
[a]This estimate is based on data collected as part of the baseline panel survey, a five-year study of over 3,700 Self-Help borrowers.
AMI = area median income (median income of the metropolitan statistical area [MSA] or the state for non-MSA areas).

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), although much larger numbers of borrowers (16.8 percent) and their spouses or partners (59.3 percent) had experienced at least one spell of joblessness lasting a week or more since closing on their loans (table 1).[11] The phenomenon of high labor market volatility and job churning among low- and moderate-income borrowers during periods of economic decline, characterized by cutbacks in overtime and the loss of second jobs and paid spousal work, contributes to higher rates of late and missed mortgage payments among all low- and moderate-income families. Those with single wage earners are particularly affected. Because these 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 are more likely to have a harder time catching up. This puts even more pressure on servicers whose portfolios contain large numbers of affordable mortgages and explains why technology that enables servicers to identify which borrowers are most likely to fall farther behind once they miss a single payment can be a valuable default management tool.

The delinquency experiences of Self-Help mortgages

As of March 2005, about 2 percent of all loans in the Self-Help portfolio had reached foreclosure. In fact, compared with industry benchmarks, Self-Help loans perform quite well. As of the first quarter of 2005, 3.03 percent of Self-Help loans were more than 90 days delinquent or in foreclosure, compared with 1.89 percent for all loans, 5.15 percent for FHA loans, and 5.23 percent for subprime loans (Mortgage Bankers Association 2005). Taken in combination with Self-Help's historical loss severity rate of just 26 percent of the original loan balance compared with 37 percent for similar FHA loans (HUD 2005), this performance suggests that Self-Help's loss mitigation efforts are effective.

Consistent with preventive servicing's emphasis on early intervention, only 10 percent of loans that became at least 30 days delinquent eventually reached foreclosure, compared with almost 30 percent that became 60 or more days delinquent. For those going over 90 days, more than 40 percent reached foreclosure.

Because this article deals with servicing and default management rather than with originations and the assessment of initial credit risk, we are more

[11]Postpurchase joblessness among spouses includes those who are not in the labor force.

interested in examining the outcomes of Self-Help loans once they become 30 days past due than we are with determining the factors that cause loans to become delinquent in the first place. (The analysis of initial delinquency and overall Self-Help loan performance is the subject of other papers produced by the Center for Community Capitalism [Quercia et al. 2002, for example].) Since the failure rate for a Self-Help loan that is over 90 days delinquent is more than four times higher than it is for one that is 30 days delinquent, we focused on the transitions within this period. From the payment history, we were able to determine when a loan became delinquent, generating a "delinquency spell." Between September 1998 and December 2004, we tracked the performance of 28,131 Self-Help loans originated before December 2003. Only 21.2 percent—or 5,969 loans—ever experienced a delinquency spell: 15.7 percent experienced only relatively mild delinquency (a delinquency spell of 30 or 60 days), and 6.7 percent experienced at least one spell lasting at least 90 days.

The servicing challenge associated with affordable lending can be more graphically illustrated by examining the number of delinquency spells generated by each loan. As table 2 shows, a large share of the ever-delinquent loans (2,564 out of 5,969) generated only one delinquency spell each, lasting an average of 2.5 months, before curing or defaulting. The remainder of these loans experienced two or more separate delinquency spells. This includes 1,403 repeatedly delinquent loans with four or more spells. While accounting for about 5 percent of all loans, this group generated over half of all delinquency spells.

A delinquency spell can be cured or progress to a 90-day delinquency (hereinafter referred to as "default"). Since most delinquency spells resolve

Table 2. Number of 30-Day Delinquencies

	Number of Loans	Percentage	Average Length of Delinquency
Never delinquent	22,162	78.8	
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	2.55 months

Source: Self-Help database and authors' calculations.

one way or the other within six months and our observation period lasted more than six years,[12] nearly all spells (97.4 percent) achieved an outcome of either cure or default before the end of the observation period. Loans that were still delinquent at the end of the period were excluded from our sample.[13] Once a loan was cured, any subsequent delinquency generated a new spell. An observation was considered cured if the loan was paid off while still 30 to 60 days delinquent.[14]

As a result, we have a sample of 15,038 delinquency spells that were generated by 5,886 borrowers and ended in either cure or default by December 2004, for an average of 2.6 delinquency spells per loan. Some 85 percent of these delinquency spells were cured, while 15 percent ended in default.[15] The 2,200 defaults were generated by 1,870 loans,[16] representing just 7 percent of all loans tracked but 31 percent of all ever-delinquent loans (table 2). The other 69 percent of ever-delinquent loans never proceeded beyond 60 days past due. Delinquency spells that cured or defaulted lasted an average of 2.1 months or 4.1 months, respectively.

As table 3 shows, 13.4 percent of first-time delinquencies ended in default, and this rate generally increased with the number of prior delinquencies, to 17.6 percent of those experiencing a fourth delinquency spell. Yet somewhat surprisingly, the default rate for borrowers experiencing a fifth or higher delinquency spell dropped to 14.2 percent, nearly identical to the default rate among loans experiencing a first spell. This finding suggests an inflexion point above which the number of previous delinquencies experienced by serially delinquent borrowers does not increase the likelihood that the current spell will end in default. In fact, smart servicing technologies seek to identify those frequently delinquent borrowers who are unlikely to actually default, saving collections resources to focus on other, higher-risk delinquencies.

We want to determine the extent to which delinquency outcomes are affected by the loan servicer. The average number of delinquency spells per

[12]Since some loans were originated after September 1998, the average length of observation for all loans is about 53 months.

[13]Because the ending date of the observation period was arbitrarily determined, the status of "still 30 or 60 days delinquent" was not considered as an independent outcome. Besides, there are very few spells in this category (2.6 percent).

[14]To make sure that a large number of early-stage delinquencies were not driven by pending refinancing plans, we examined the number of delinquencies that ended in repayment. However, only 234, or less than 2 percent, of delinquency spells ended in payoff.

[15]We use 90 days as a proxy for default because completed defaults usually lag substantially and the data provide more occurrences of delinquencies exceeding 90 days. The measure, then, is to what extent loans move to the more severe category of "serious delinquency" or more than 90 days late.

[16]Some 90-day delinquent loans cured and then subsequently became delinquent again.

Table 3. Percentage of 30-Day Delinquencies That End in Default (by Delinquency Order)

	Number of Spells	Number of Defaults	Percentage
First delinquency	5,886	786	13.4
Second delinquency	3,327	520	15.6
Third delinquency	2,097	319	15.2
Fourth delinquency	1,345	236	17.6
Fifth or higher delinquency	2,383	339	14.2
Total	15,038	2,200	14.6

Source: Self-Help database and authors' calculations.

servicer in the population is 537. Eight servicers had in excess of this average; we classified these as the "main servicers." Four of these accounted for more than 1,000 of the delinquency spells each, while the other 4 serviced between 537 and 1,000. The remaining 20 servicers each managed less than the average number of spells; at the far end of the spectrum were several who handled less than 50. Table 4 shows the number and outcomes of delinquency spells for the eight main Self-Help servicers, which together managed 83 percent of the delinquency spells we tracked (and 76 percent of the 5,886 loans), and for all others combined. The main 8 servicers were not necessarily larger than the other 20; in fact, some were quite small. They simply had a larger share of the Self-Help loans that experienced delinquency spells.

Table 4 shows that Servicers 2, 6, and 7 exhibit the lowest cure rates (below 80 percent) while Servicers 1, 5, and the "others" category have the highest (just around 90 percent). These are naturally accompanied by higher and lower default rates, respectively. In between are Servicers 3 and 4, which fall closer to the latter group, and Servicer 8, which falls closer to the former.

Most of the loans were serviced by the same entity that originated them. However, there were two cases where an originator used more than one servicing operation. We found that in one of these cases, there was a measurable difference in cure rates (9.6 percent versus 12 percent) between the two servicers used. In the other case, where one of the subservicers handled one-twentieth as many loans as the other, both had nearly identical cure rates

Table 4. Outcomes of 30-Day Delinquencies by Servicer

	Number of Loans	Number of Delinquencies	Percent Cured	Percent 90 Days Delinquent
Servicer 1	293	656	88.87	11.13
Servicer 2	594	1,461	79.19	20.81
Servicer 3	1,133	3,474	86.70	13.30
Servicer 4	824	2,594	87.24	12.76
Servicer 5	377	861	90.36	9.64
Servicer 6	595	1,688	77.84	22.16
Servicer 7	261	599	79.63	20.37
Servicer 8	405	864	83.91	16.09
Others	1,404	2,841	89.02	10.98
Total	5,886	15,038	85.37	14.63

Source: Self-Help database and authors' calculations.
Note: Eight major servicers (handling more than the average number of delinquencies) were chosen for inclusion in our analysis.

(12.2 percent and 12.5 percent). In both of these cases with one originator and multiple servicers, there was only one servicer with a large enough number of delinquency spells to be counted among the main ones; the rest were included in the others category. In all other cases, a single, unique servicer was managing a portfolio of loans originated by the same lender.

Logit regression model

To better isolate the impacts of different servicing methods and other risk factors, our goal in modeling the outcomes of the 15,038 delinquency spells is to identify factors that predict the likelihood that a given delinquency will cure or worsen and go into default. We model the binary outcomes using a logit regression approach where the dependent variable is the odds of cure and the reference category is default.

$$Log\left[\frac{p_i}{1-p_i}\right] = \alpha + \sum_{j=1}^{k} \beta_j X_{ij} \qquad (1)$$

Here, P_i is the probability of transition from a 30-day delinquency to cure, X_i is a column vector of the covariate measures for delinquency spell *i*, and β is a row vector of coefficients for the outcome of curing. This model assumes that outcomes at any one point in time are independent of outcomes in any previous point in time. To control for the potential statistical problems associated with repeated events, the model was estimated using Stata's logit procedure with an adjustment to the standard errors for clustering by loan.[17]

In addition to investigating the outcomes for all delinquency spells, it is also important to look at the outcomes of the first delinquency spells to eliminate the effect of possible dependence among different spells. It is possible that some servicers could treat first delinquencies differently from serial ones. To check the different impact of servicers on the outcome of first delinquencies, we used the same model to run a separate regression on first delinquency spells.

We recognize that differences in cure and default rates may be due to differences in the composition of each portfolio. Table 5 profiles the loans handled by the main eight servicers and all others. The differences are notable: Servicer 6's portfolio has the greatest share of low credit scores and the lowest-income borrowers. Loans handled by Servicer 8 have especially high LTVs, while loans handled by Servicer 5 experienced the highest housing appreciation rates during the study period. As to the loans serviced by "others," the only obvious difference in terms of risk factors is in their somewhat better appreciation rates (7 percent versus 4 percent for all but Servicer 5). Borrowers serviced by the others category also have higher income than borrowers handled by most of the main eight.

Consequently, when we estimate the logit regression model, we control for various loan and borrower characteristics that might affect delinquency outcomes. Control variables in the model include the following:

1. *Loan characteristics*. Housing equity is a key factor in determining default. Delinquent borrowers with substantial accumulated equity have more resources to avoid foreclosure, while those with little or no equity have less incentive and less ability to retain their home. We include a dummy variable for loans with an LTV of 95 percent or higher. We also include loan age in months at the time of delinquency and the number

[17]The estimation used the "cluster" option, which specifies that observations are independent across groups (loans) but not necessarily within groups (Stata Corporation 2003). This option affects the estimated standard errors and variance-covariance matrix of the estimator, but not the estimated coefficients.

Table 5. Loan and Borrower Characteristics by Servicer

		Main Servicers								
Variable	All	1	2	3	4	5	6	7	8	Others
Credit score										
No credit score (%)	3.5	0.3	4.4	0.6	1.2	2.27	7.7	7.1	1.3	5.78
FICO 620 or lower (%)	17.2	7.8	23.1	25.1	23.8	9.42	46.5	26.4	15.5	11.43
FICO 621 to 660 (%)	21.0	17.6	26.5	20.4	23.7	20.61	21.3	35.1	20.2	19.41
FICO 661 to 720 (%)	30.4	33.7	29.1	26.8	29.9	37.22	15.2	22.4	36.5	30.88
FICO above720 (%)	28.0	40.6	17.0	27.1	21.5	30.49	9.3	9.2	26.6	32.50
Loan characteristics										
Median LTV (%)	97.0	97.0	97.0	97.0	99.0	97.0	97.0	97.0	102.3	97.0
Median back-end ratio (%)	36.7	37.7	37.5	35.4	36.6	37.3	34.9	37.1	37.2	37.0
Age of loan at purchase (months)	11	13	3	23	18	9	5	2	9	12
Estimated appreciation rate (%)[a]	4.3	4.2	3.3	3.4	3.6	13.4	4.1	4.0	4.4	7.0
Borrower characteristics										
Female borrower (%)	44.0	43.3	48.7	51.1	46.03	36.71	50.1	37.5	43.2	37.14
Black borrower (%)	21.3	15.2	33.9	34.7	37.66	9.88	60.2	12.5	6.8	13.50
Hispanic borrower (%)	16.6	4.8	4.2	2.6	2.89	42.98	2.0	7.9	15.1	26.56
First-time home buyer (%)	43.8	56.0	18.0	64.8	88.61	32.09	82.4	18.0	48.3	25.39
Income at origination ($) (median)	29,472	31,074	30,000	23,640	24,870	35,634	24,504	30,276	27,996	33,516
Income as a percentage of AMI (median)	59.7	61.3	64.3	57.0	58.1	61.2	48.2	52.8	59.8	61.8
Total loans[b]	28,131	1,962	1,852	4,661	2,318	2,378	1,055	850	2,464	10,591

Source: Self-Help database and authors' calculations.
Note: Totals may not equal 100 percent because of rounding.
[a] The estimated annual house appreciation rate is based on the house price at origination and the updated house prices estimated in December 2005.
[b] Self-Help loans purchased before January 1, 2003.
AMI = area median income (median income of the metropolitan statistical area [MSA] or the state for non-MSA areas).

of previous delinquencies (of course, this variable is not included in the model focusing on the transition of first delinquencies).

2. *Borrower characteristics*. To control for underwriting and borrower differences, we include a dummy for back-end ratios of 38 percent or higher,[18] income as a percentage of area median income, dummies for gender and race/ethnicity, and a dummy for first-time home-buyer status. Since the impact of credit score on loan performance might not be linear, we follow industry practice and previous literature by also including a set of credit score dummy variables for borrowers with no credit score, borrowers with low scores (below 620), borrowers with moderate scores (620 to 659), and borrowers with relatively high scores (660 to 719). The category with the highest scores (720 or above) is set as a reference group.

3. *Economic conditions*. Because changes in property values after origination can affect housing equity, we use a variable for the estimated annual rate of appreciation, determined using the change between the value of the house at origination and updated values for each property as of December 2005. To help separate lender/servicer effects from regional economic effects, we also include dummy variables for the states having the most loans in the Self-Help population studied: North Carolina and California.

To test for differences among servicers, we incorporate dummy variables for the main eight Self-Help servicers into our logistic model. We treat delinquencies served by "others" as the reference group. The odds ratio estimated from the model is the odds of cure (versus worsening) of a delinquency spell for one servicer relative to the odds of cure by servicers in the others category. Table 4 indicated that the reference group ("others") had a very high cure rate (89.02 percent); only Servicer 5 had a higher rate than this. In other words, after controlling for other characteristics in our logit model, we are comparing the practices of major servicers with some of the best performers (as the simple frequency table suggests).

Some of the explanatory variables are highly correlated. Generally, borrowers with high LTVs have lower credit scores. Black and Hispanic borrowers also have lower credit scores and higher LTVs than non-Hispanic whites.

[18]According to the *Selling Guide* created by Fannie Mae, its suggested benchmark for total debt-to-income ratio is 36 percent for standard loans and 38 percent for community lending products (Allregs.com 2006). Nearly all Self-Help lenders allow a higher maximum ratio, ranging from 40 percent to 48 percent.

Properties in California have higher house appreciation rates. Further, there is a significant correlation between the loan age variable and the number of previous delinquencies. However, these variables have been widely used in the literature, and a check of variance inflation factors indicates that multicollinearity is not particularly serious among independent variables.[19] As a result, the final model of this analysis includes all these important variables such as credit scores, LTV, race, gender, and state dummies.

Tables 6 and 7 present the results of the logit regression model. Table 6 is based on all delinquency spells, while table 7 focuses on the transition of first delinquency spells only.[20] A positive coefficient means that the odds of cure increase as the independent variable increases; a negative coefficient means that the odds decrease. An odds ratio represents the odds of cure when an independent variable is equal to 1 relative to the odds of cure for the reference category (for categorical variables). The model fit is strong.[21] Further, the eight servicer variables were jointly significant at the 0.001 level, which suggests that the introduction of these variables appreciably increases the explanatory power of the model.

Of primary interest is the fact that after controlling for loan and borrower characteristics, house appreciation rate, and regional dummies, we find significant differences in the odds of cure among servicers. Specifically, delinquencies for Servicers 2, 3, 6, and 7 are significantly less likely to cure than they are for the servicers in the others category, while the odds of cure for Servicers 1, 4, 5, and 8 are not significantly different from those "others." In other words, 30-day delinquencies for Servicers 2, 3, 6, and 7 are significantly more likely to end in default than they are for servicers in the others category. The odds of cure for Servicers 2, 6, and 7 are about 40 percent lower than they are for servicers in the others category, while the odds are about 20 percent lower for Servicer 3.

[19]Variance inflation factors are a measure of the multicollinearity in a regression design matrix. For this study sample, the variance inflation indicators for most variables are less than 3 (generally considered acceptable). The only exceptions are several categorical credit score variables.

[20]The final study sample for table 6 is reduced from 15,308 to 13,878 because of missing data. The study sample for table 7 is 5,443.

[21]To assess the predictive quality with the model focusing on all the spells, we find that the share of correctly predicted observations was 87 percent for cure and 23 percent for default if we specify the cutoff as > 0.8 (an estimated probability of > 0.8 for cure would be assigned to be a positive outcome). The overall share of correctly classified observations is 78 percent. Of course, a higher cutoff would lead to better specification for default and poorer sensitivity for cure. For example, if the cutoff is set as 0.85, the share of observations that were correctly predicted is 67 percent for cure and 47 percent for default. The overall correctly classified share is 64 percent.

Table 6. Logistic Regression Results for the Outcomes of 30-Day Delinquencies: Probability of Cure

Variable	Coefficient	Standard Error	Odds Ratio
Constant	1.423**	0.193	
No credit score	–0.349*	0.102	0.705
FICO below 620	–0.046	0.119	0.955
FICO 620 to 659	0.031	0.131	1.032
FICO 660 to 719	0.036	0.136	1.036
LTV 95 or above	–0.087	0.069	0.917
Female borrower	0.128*	0.066	1.136
Black borrower	0.076	0.071	1.079
Hispanic	0.301**	0.163	1.351
Income as a percentage of AMI	0.006**	0.002	1.006
Age of loan (months)	0.004**	0.001	1.004
Number of previous delinquencies	–0.028	0.014	0.973
Appreciation rate[a]	0.028**	0.010	1.028
North Carolina borrower	0.119	0.104	1.126
California borrower	–0.101	0.176	0.904
Servicer 1	0.121	0.193	1.129
Servicer 2	–0.610**	0.072	0.543
Servicer 3	–0.222*	0.088	0.801
Servicer 4	–0.213	0.099	0.808
Servicer 5	0.088	0.157	1.093
Servicer 6	–0.545**	0.068	0.580
Servicer 7	–0.527**	0.086	0.590
Servicer 8	–0.235	0.109	0.790
Model fit			
Wald_^{2}	209.2**		
df	22		

Source: Self-Help database and authors' calculations.
Note: The study sample is 13,878 since a number of observations were dropped because of missing data.
[a] The estimated annual house appreciation rate is based on the house price at origination and updated house prices estimated in December 2005.
AMI = area median income (median income of the metropolitan statistical area [MSA] or the state for non-MSA areas).
$^*p \leq 0.05$. $^{**}p \leq 0.01$.

Table 7. Logistic Regression Results for the Outcomes of the First 30-Day Delinquencies: Probability of Cure

Variable	Coefficient	Standard Error	Odds Ratio
Constant	1.553**	0.26	
No credit score	–0.375	0.164	0.687
FICO at or below 620	–0.057	0.162	0.945
FICO 620 to 659	0.005	0.175	1.005
FICO 660 to 719	0.070	0.191	1.073
LTV 95 or above	–0.099	0.105	0.906
Female borrower	0.342**	0.125	1.408
Black borrower	0.143	0.116	1.154
Hispanic	0.237	0.209	1.267
Income as a percentage of AMI	0.008**	0.003	1.008
Age of loan (months)	–0.003	0.002	0.997
Appreciation rate[a]	0.026**	0.010	1.027
North Carolina borrower	0.070	0.154	1.073
California borrower	0.072	0.298	1.074
Servicer 1	–0.199	0.184	0.820
Servicer 2	–0.547**	0.118	0.578
Servicer 3	–0.135	0.152	0.874
Servicer 4	–0.085	0.174	0.919
Servicer 5	0.216	0.292	1.241
Servicer 6	–0.949**	0.066	0.387
Servicer 7	–0.894**	0.081	0.409
Servicer 8	–0.472**	0.115	0.624
Model fit			
Wald _^{2}	161.4**		
df	21		

Source: Self-Help database and authors' calculations.
Note: The study sample is 5,443 since a number of observations were dropped because of missing data.
a The estimated annual house appreciation rate is based on house price at origination and updated house prices estimated in December 2005.
AMI = area median income (median income of the metropolitan statistical area [MSA] or the state for non-MSA areas).
*$p \leq 0.05$. **$p \leq 0.01$.

As to the control variables, it is particularly noteworthy that variables that are key indicators of default risk at the time of underwriting (based on credit score and LTV) generally do not appear to be significant in predicting whether an already delinquent loan will default. The only exception is that there is some evidence that borrowers without credit scores are less likely to be cured. But some borrower characteristics do matter. Female, Hispanic, and higher-income borrowers are more likely to cure. In particular, delinquent borrowers who were Hispanic had 39 percent better odds of curing (versus worsening) than delinquent borrowers who were white. The evidence also indicates that older loans are more likely to cure, suggesting that experienced borrowers handle delinquencies better than new ones do. From a macroeconomic standpoint, location in either North Carolina or California did not have a significant effect on outcomes, but there is considerable evidence that the higher the house appreciation rate, the more likely that delinquent loans would be cured and the less likely that borrowers would let the delinquency proceed.

When we focus on the first delinquency spell (table 7), the results are generally consistent with the results based on all delinquency spells. First delinquencies for Servicers 2, 6, and 7 are still less likely to be cured, while the coefficients for Servicer 3 become insignificant, like those of Servicers 4 and 5. But the coefficient for Servicer 8 is significant and negative in this model. Among Servicers 2, 6, 7, and 8, the odds of cure are particularly low—about 60 percent lower— for Servicers 6 and 7. Thus it seems that the relative odds of cure for these servicers, while worse for all delinquencies, lag even more for first delinquencies.

Table 8 shows predicted cure and default rates by servicer. Using the results from table 6 (all spells), we estimate that Servicer 2 has the lowest predicted cure rate (and the highest predicted default rate), while Servicer 1 has the highest predicted cure rate (and the lowest predicted default rate). In other words, the probability that a delinquent loan serviced by Servicer 2 will default is nearly double that for Servicer 1 (table 8).

Thus there appear to be roughly two groups of servicers in terms of outcomes. Delinquencies handled by Servicers 2, 3, 6, and 7 have a lower probability of cure and a higher probability of default. Servicers 1, 4, 5, and 8, along with the servicers in the others category, have higher cure rates and a lower risk of default.[22]

[22]Although Servicer 8 has a lower cure rate for the first-30 delinquency spells, its overall cure rate is not statistically different from that of the "others."

Table 8. Predicted Outcomes of a Typical 30-Day Delinquency by Servicer

	Percent Cured	Percent in Default (90 Days Delinquent)
Servicer 1	90.41	9.59
Servicer 2	81.94	18.06
Servicer 3	87.00	13.00
Servicer 4	87.10	12.90
Servicer 5	90.13	9.87
Servicer 6	82.89	17.11
Servicer 7	83.13	16.87
Servicer 8	86.84	13.16
Others	89.31	10.69

Source: Self-Help database and authors' calculations.
Note: Based on the logit regression model in table 6. Additional borrower and loan characteristics have been controlled for.

From telephone interviews with the main servicers and supplemental information provided by Self-Help's Servicing Manager, we learned that there are significant differences in the way personnel, systems, and processes are applied to nonperforming loans between the 30th and 90th day of delinquency—the period reflected by the analysis (Russell 2005). For example, one servicer has one collector for every 15,000 loans it services and uses no risk-scoring system at all. This is in stark contrast to the servicers that have at least one collector for every 5,000 loans and use both collections scoring and foreclosure alternative assessment models, supported by scripting software.

Servicers use a number of different collections and loss mitigation tools. Collections scoring tools include Freddie Mac's EI and Fannie Mae's RP. EI features both a score that prioritizes calls to borrowers in the early stage of delinquency and a module that predicts the share of more advanced delinquencies that could result in a loss (Freddie Mac n.d.). RP uses borrower, loan, and property characteristics to segment loans (whether currently delinquent or not) by likelihood of going more than 60 days delinquent within six months. Investors have laid out specific servicing procedures based on score—for example, recommending earlier contact for high-risk rather than for low-risk loans (Fannie Mae 2005a, 2005b). Tools to assess alternatives to foreclosure include Freddie Mac's Workout Prospector®, which applies a consistent approach to assess the viability of foreclosure alternatives for each case (Cutts and Green 2005), and Workout Profiler™, part of Fannie Mae's Home Saver Solution Network™ (HSSN), a Web-based, interactive model that incorporates such data as financial situation, property value, and payment history (O'Connor 2003). An example of a scripting system is EarlyResolution®,[23] a program to train and guide personnel as they interact with borrowers to determine the best method to help them keep their homes (O'Connor 2003).

Servicers also follow different steps to address delinquencies. Self-Help suggests that its subservicers follow a specific timeline through the delinquency process (figure 1). But while servicers generally followed Self-Help's manual, there were some marked deviations in actual delinquency management.

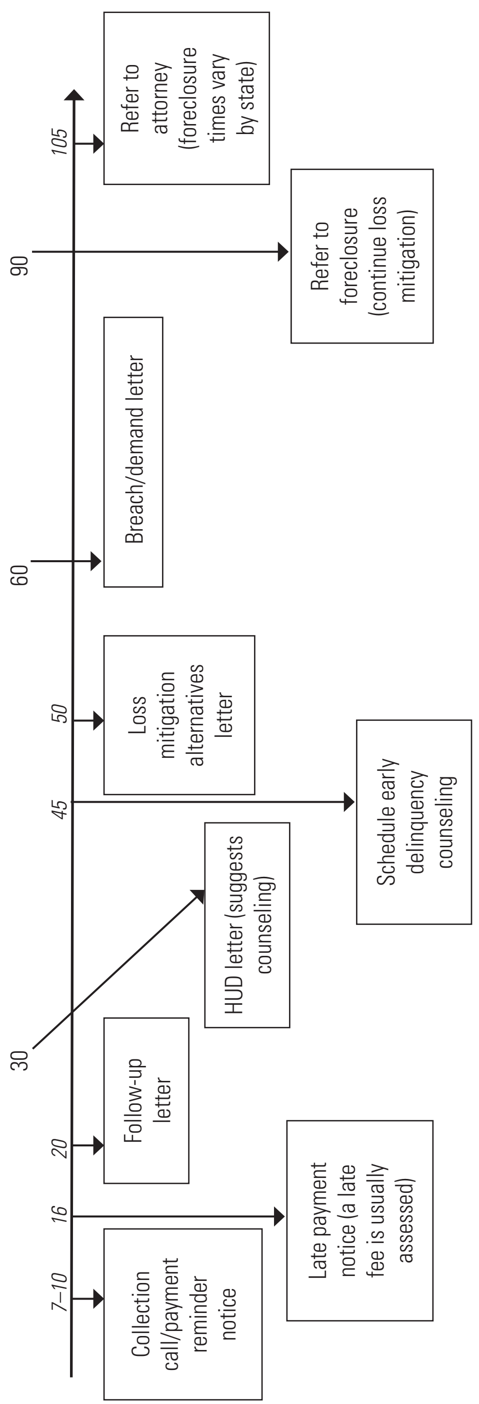
Another area of differentiation derives from a Self-Help- driven delinquency intervention program. In the traditional process, the borrower must take some initiative to get into a loss mitigation plan, either by contacting the servicer or a housing counselor or by filling out an information packet that comes in the mail from the servicer. In 2002, Self-Help began testing a more proactive approach by engaging Balance, an affiliate of Consumer Credit Counseling of San Francisco, to contact borrowers by telephone on the 45th day of delinquency. The program was activated with Servicers 1, 2, 3, and 6 between 2002 and late 2003, as well as with one other that is not profiled in this article (Holder 2005). Because Self-Help deliberately phased in servicers according to where intervention might have the most impact, it is not surprising that most of the participating servicers fall in the lower cure rate category.

Servicer profiles

Profiles of the different staffing, systems, and processes used by the main Self-Help servicers are described in the following paragraphs. These servicers and subservicers ranged in size from less than 50,000 loans serviced to 2 million. They are located in various parts of the country, and their portfolios include loans from many different states. They do not focus strictly on conventional, affordable mortgages, but rather service a range of mortgage types. So while not statistically representative of all servicers, these brief case studies characterize a wide range of institutions, practices, and foreclosure prevention strategies. Whether one of these strategies is more effective or

[23]This program was developed on a third-party platform. Freddie Mac sold it to the third party, Computer Sciences Corporation, in 2004 (Computer Sciences Corporation 2004).

Figure 1. Self-Help Delinquency Management Timeline in Days



Source: Center for Community Self-Help (2003).

efficient than another cannot be determined from this analysis, but the extent of the differences hints at why outcomes vary.

Servicers 1, 4, 5, and 8 (higher cure rates). Servicer 1 is a midsize organization (between 100,000 and 300,000 loans serviced in all) that uses EI for delinquency scoring. There is a strong collections staff, with one collector for every 4,000 loans in the portfolio. This enables specialization such that two collectors are assigned to Self-Help loans. They follow Self-Help's timeline closely. In terms of loss mitigation, however, Servicer 1 has only one specialist to address its portfolio of more than 100,000 loans and does not use a workout system. Self-Help rolled out its delinquency intervention pilot with this servicer 15 months before the end of the 53-month observation period, so it would have a somewhat limited impact on our results.

Servicer 4 is a mega-servicer (more than 1 million loans handled). It averages 20,000 loans per collector; also, it outsources certain calls for early-term, low-risk delinquencies and uses both RP and EI. Affordable mortgages are not identified per se, but investor process requirements are followed for all loans. Servicer 4 also averages about 20,000 to 25,000 loans per loss mitigation employee and uses a proprietary workout system but no scripting technology. This is one of only two servicers that reported paying an incentive to its loss mitigation staff, in this case for workouts that are approved or closed.

Servicer 5, also a mega-servicer, uses both RP and EI and has a loans-to-collector ratio that falls at the higher end of the range among Self-Help's servicers. Staff members specialize by investor, not product type. For loss mitigation, the servicer uses the HSSN and supplements decision making with internally developed spreadsheets. This servicer's process is somewhat unusual in that it starts collections calling on day 1 and sends the loss mitigation alternatives letter very early—on the 30th day—even in advance of the HUD letter. (The HUD letter gives the borrower a toll-free number to call to obtain the name, number, and address of the nearest HUD-approved counseling agency. The loss mitigation letter informs the borrower that he or she may qualify for alternatives to foreclosure. The letter lists options (repayment plan, loan modification, deed in lieu, and preforeclosure sale) and provides a description of what each one means.) This likely encourages workouts early in the delinquency timeline.

Servicer 8 is small (less than 100,000 loans) and uses RP. Overall, it staffs one collections person per 6,000 loans, with one collector assigned to its 2,000 affordable loans (including Self-Help). The loss mitigation employees—about one for every 20,000 loans in the portfolio—do not specialize; Workout Profiler^{TM} is used for loss mitigation (Russell 2005). From a process standpoint, Servicer 8 takes little action between the initial delinquency letter and the 60th day, when the HUD letter, loss mitigation letter, and breach letter are all sent within a few days of each other (Holder 2005).

Servicers 2, 3, 6, and 7 (lower cure rates). Servicer 2 is small and has one collections person for every 15,000 loans and no risk scoring system. There is only one loss mitigation counselor (for about 50,000 loans), and the HSSN is used for workouts. Staff members do not specialize by investor or product type. Servicer 2 sends out the HUD letter two weeks later than suggested, but otherwise generally follows Self-Help's timeline. Because of the large number of delinquencies and its limited resources, Servicer 2 was selected as the first participant in the intervention program.

Servicer 3 is large (300,000 to 1 million loans) and uses both RP and EI. It employs approximately one collections person per 10,000 loans. Collectors do not specialize. On the loss mitigation side, there is one specialist for 80,000 loans, and the HSSN is used for workouts. Servicer 3 basically follows Self-Help's investor requirements and began participating in the intervention program in August 2002, about midway through the observation period.

Servicer 6 is another large organization. The ratio of loans serviced per collector is between 5,000 and 10,000, while the ratio of loss mitigation specialists to loans is about one per 20,000. Servicer 6 uses RP but no smart workout system. HUD letters are not sent, but a breach letter is sent very early (on the 35th day), and loans are referred to foreclosure earlier as well. This servicer has participated in the delinquency intervention program since July 2003 (the final 18 months of the observation period).

Servicer 7 falls in the mega-servicer category, averaging 12,000 loans per full-time collections employee. This servicer reports having a dedicated team for higher-risk products; making introductory calls when new loans in this category are added to the portfolio; paying staff incentives for workouts; and using RP, EI, multiple loss mitigation systems, and a scripting system. This servicer's actual process is distinct in that neither a HUD letter nor a loss mitigation letter is automatically sent, and the breach letter does not go out until the 90th day, so there often appears to be little communication with delinquent borrowers between the 30th and 90th days.

Evidently, there is substantial variation in the servicers' approaches to foreclosure prevention—so much, in fact, that it is difficult to discern best practices. We believe that this variation is not confined to the Self-Help servicers, but speculate that it is widespread, particularly as sales, mergers, and consolidations result in the realignment of servicing platforms and cultures. Further research into successful strategies for affordable mortgages could help servicers develop more effective combinations of people, processes, and technology that would help a greater number of troubled borrowers keep their homes.

Conclusions

The unprecedented growth in homeownership among low- and moderate-income families during the 1990s meant that the back end of the home-buying transaction—loan servicing and postpurchase default management—became much more important. Although delinquency and default rates increased as the economy fell into recession, many more financially squeezed homeowners would possibly have lost their homes if not for the innovations in loan servicing discussed in this article. At this writing, the looming possibility of softening housing markets and rising foreclosures, and the proliferation of aggressive mortgage products with adjustable rates and negative amortization suggest that these tools may become even more important in the near future. For example, interest-only loans, on which no principal payments are made to bring down mortgage debt, made up nearly one-third of mortgage originations during 2004 and 2005 (Fishbein and Woodall 2006). According to one estimate, of the 7.7 million households that took out adjustable-rate mortgages to buy or refinance in 2004 and 2005, "up to 1 million could lose their homes through foreclosure over the next five years because they won't be able to afford their mortgage payments, and their homes will be worth less than they owe" (Knox 2006, A1).

As mortgage products featuring more flexible underwriting standards gain in popularity and as more low- and moderate-income families, immigrants, and minorities join the first-time home-buying market, the economic fortunes of mortgage institutions will be increasingly tied to the effectiveness of their loan servicing operations. Clearly, the more aggressive the underwriting, the more important preventive servicing becomes. While close coordination between credit underwriting policies and servicing strategies is important for the entire industry (Caldwell and Jordan 2006), it is even more important for affordable housing portfolios.

Although it is not possible to generalize for all affordable lending programs, early findings from our evaluation of the Self-Help secondary market demonstration program are nevertheless suggestive. A significant share of Self-Help borrowers and coborrowers who bought their homes before the onset of the 2000- 01 recession have experienced multiple spells of joblessness and missed housing payments since taking out their loans. Yet the vast majority of Self-Help borrowers have never missed a payment, and a small fraction account for a disproportionately large share of total delinquency spells and defaults.

Against this overall backdrop, we find that even after controlling for loan and borrower characteristics and regional economic conditions, the odds that a late-paying borrower will manage to catch up on payments instead of sinking into serious delinquency can vary as much as 60 percent between servicers. This suggests that servicing strategies do matter.

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 notwithstanding. Some servicers we interviewed still value personnel over technology. While this may be a wise choice in the short run, without the decision-making technology that will become the industry standard, affordable lenders will lag behind industry benchmarks over the long term, and more low- and moderate-income borrowers than necessary will lose their homes.

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. The evidence that preventive servicing really works should spur foundation and government support for the dissemination of best practices. For example, foundation and government grants for access and training could accelerate the rate at which these smart servicing systems are adopted by smaller lenders and servicers of affordable mortgages. And this, in turn, could make their preventive servicing efforts smarter and more cost-effective.

Finally, policy aimed at affordable homeownership should be more symmetrical; mortgage innovations that lower the cost of entry must be matched by support for more sophisticated servicing systems. In the research realm, there is an urgent need for systematic, firm-level studies of servicing practices for affordable mortgages. As the present study suggests, without being able to "unbundle" servicing activities and observe how firm-level practices are actually implemented, defining best practices will be impossible.

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