Risky Borrowers or Risky Mortgages Disaggregating Effects Using Propensity Score Models

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Abstract This paper examines the relative risk of subprime mortgages and community reinvestment loans originated through the Community Advantage Program (CAP). A sample of comparable borrowers with similar risk characteristics is constructed using the propensity score matching method but holding two different loan products. The findings reveal that the sample of community reinvestment loans has a lower default risk than subprime loans, very likely because they are not originated by brokers and lack risky features such as adjustable rates and prepayment penalties. Results suggest that similar borrowers holding more sustainable products exhibit significantly lower default risks.

One major concern after the collapse of the subprime mortgage market is whether the efforts to extend credit to lower-income and minority homebuyers will fall out of favor. Different from the high-risk subprime lending, there are some special lending programs targeting low-income and minority population with safe and sound operation in the residential mortgage market, such as Community Reinvestment Act (CRA)-motivated lending. The CRA directs depository institutions to help meet the credit needs of all segments of their local communities. Studies have shown that CRA has increased the volume of lending to low- and moderate-income households (Apgar and Duda, 2003; Avery, Courchane, and Zorn, 2009), while most subprime loans were originated by lenders not covered by CRA (Avery, Brevoort, and Canner, 2007a).

What is missing in the debate on the subprime crisis is an empirical examination of the relative performance of similar borrowers holding either a typical CRA-related loan or a subprime product. Such an analysis will help inform policy by answering the question of whether CRA-type mortgages contributed significantly to the housing crisis. Since borrowers holding CRA-type mortgages generally had higher levels of credit risk, such study also helps to answer the question of whether the high default rates of subprime loans represent just the higher risk profile of borrowers holding these loans or the risky characteristics of subprime loans. Some products or features that are more prevalent among subprime loans, such as prepayment penalties, adjustable rates, and balloon payments, have been found to be associated with elevated default risk (e.g., Ambrose, LaCour-Little, and Huszar, 2005; Quercia, Stegman, and Davis, 2007; Pennington-Cross and Ho, 2010). Are the higher default rates reported in the subprime sector mainly the result of risky loan products?

This study compares the performance of subprime loans and CRA loans in a special lending program called the Community Advantage Program (CAP). Since performance differences may be due to differences in credit risk of borrowers who receive different product type, propensity score matching methods is used to construct a sample of comparable borrowers. The findings reveal that for borrowers with similar risk characteristics, the default risk will be about 70% lower with a CAP loan than with a subprime mortgage. Broker-origination channel, adjustable rates, and prepayment penalties all contribute substantially to the elevated risk of default among subprime loans. When broker origination is combined with both adjustable rates and prepayment penalties, the borrower's default risk is four to five times higher than that of a comparable borrower with a prime-term CRA mortgage. Though CAP has some program-specific characteristics, the results of this study clearly suggest that mortgage default risk cannot be attributed solely to borrower credit risk; the high default risk is significantly associated with the characteristics of loan products. Done responsibly, targeted lending programs stimulated by the CRA can do a much better job of providing sustainable homeownership for the low- to moderate-income (LMI) population than subprime lending. The results have important policy implications for how to respond to the current housing crisis and how to meet the credit needs of all communities, especially those with large fraction of LMI borrowers, in the long run.

Compared to prior work, this study is characterized by several important differences. First, while most early studies focused on the performance of mortgages within different markets, the focus here is on similar LMI borrowers with different mortgages, and the relative risk of the different mortgage products. Second, because of data constraints, research on the performance of CRA loans is scarce. With a unique dataset, this study examines the long-term viability of the homeownership opportunities that CRA-type products provide, relative to that of subprime alternatives. Finally, there have been few discussions and applications of the propensity score matching method in real estate research. This study uses propensity score models to explicitly address the selection bias issue and constructs a comparison group based on observational data. This method allows isolation of the impact of loan product features via the origination channel on the performance of mortgages.

The recent studies on the risk of subprime mortgages and CRA lending are reviewed next. The discussion then continues to the data and method used to compare the mortgage performance of a national sample of subprime and CRA loans with similar borrower characteristics. A discussion of regression results follows. The paper closes with concluding remarks including the possible policy implications.

Literature Review

Risk of Subprime Mortgages

Subprime mortgages were originally designed as refinancing tools to help borrowers with impaired credit consolidate debt. With the reformed lending laws, the adoption of automated underwriting, risk-based pricing, as well as the persistent growth in house prices nationwide, the subprime lending channel soon expanded its credit to borrowers on other margins. The subprime surge was rapid and wide: between 1994 and 2006, the subprime share of all mortgage originations more than quadrupled, from 4.5% to 20.1%; subprime loan originations increased more than seventeen fold, from $35 billion to about $600 billion.

Beginning in late 2006, a rapid rise in subprime mortgage delinquency and foreclosure caused a so-called meltdown of the subprime market. The Mortgage Bankers Association (MBA) reports that the serious delinquency rate for subprime loans in the second quarter of 2008 was 7.6 times higher than that for prime loans (17.9% vs. 2.35%). Although subprime mortgages represented about 12% of the outstanding loans, they represented 48% of the foreclosures started during the same quarter (MBA, 2008). Delinquency and default rates for subprime loans typically are six times to more than ten times higher than those of prime mortgages (Pennington-Cross, 2003; Immergluck, 2008).

A rapid rise in high-risk subprime mortgage delinquency and foreclosure suggests there are limits to such efforts. The high default rate of subprime loans reflects the higher level of risk characteristics of borrowers holding high-risk subprime mortgages than average prime borrowers. Gerardi, Shapiro, and Willen (2007) suggest that house price decline was the primary driver of the high default rate of subprime loans in Massachusetts. Mian and Sufi (2009) conclude that the recent foreclosure mess is primarily driven by house price declines, but their results also suggest that loose underwriting in places with high latent demand is an important determinant in the price bubble in the first half of this decade and subsequent foreclosures. They suggest that the loose underwriting intended to expand the supply to borrowers, who were traditionally unable to access the mortgage market, led to a rapid increase in the risk profile of borrowers, a surge in supply-induced house price, and the subsequent spike in default rates. Demyanyk and Van Hemert (forthcoming) have shown the quality of subprime loans deteriorated for six consecutive years before the crisis. Both Demyanyk and Van Hemert (2009) and Mian and Sufi (2009) reach a similar conclusion: the unsustainable growth of the subprime mortgage market leads to the collapse of the market, which follows a classic lending boom-bust scenario.

However, it is important to make a distinction between borrowers and mortgage products. It can be said that there are two types of borrowers and two types of mortgage products: prime and subprime. Not all prime borrowers get prime mortgages and not all subprime borrowers get subprime mortgages. Borrowers who do not meet all the traditional underwriting guidelines can be considered subprime but these borrowers can receive prime-type mortgages as they may through CRA efforts. Similarly, borrowers with good credit can receive subprime products characterized by high debt-to-income and loan-to-value ratios, no or low documentation, teaser and adjustable rates, and other such risky characteristics (the so called Alt-A market).

In the literature, some loan features and loan terms are more prevalent in the subprime sector than in other markets and are also associated with higher default risk. As summarized by Cutts and Van Order (2005) and Immergluck (2008), characteristics of subprime loans relative to prime loans include: (1) high interest rates, points, and fees, (2) prevalence of prepayment penalties, (3) prevalence of balloon payments, (4) prevalence of adjustable-rate mortgages (ARMs), and (5) popularity of broker originations. After 2004, some ''innovative'' mortgage products, such as interest-only, payment option, negative amortization, hybrid ARMs, and piggy-back loans became more popular in the subprime sector (Immergluck, 2008). Quercia, Stegman, Davis, and Stein (2007) find that subprime ARMs have a higher risk of foreclosure because of the interest-rate risk. At the aggregate level, the share of ARMs appears to be positively associated with market risk as measured by the probability of the property value to decline in the next two years (Immergluck, 2008). Subprime hybrid ARMs, which usually have prepayment penalties, bear a particularly high risk of default at the time the interest rate is reset (Ambrose, LaCour-Little, and Huszar, 2005; Pennington-Cross and Ho, 2010).

As to the feature of prepayment penalties and balloons, Quercia, Stegman, Davis, and Stein (2007) find that refinanced loans with prepayment penalties are 20% more likely to experience a foreclosure than loans without while loans with balloon payments are about 50% more likely to experience a foreclosure than those without. Prepayment penalties also tend to reduce prepayments and increase the likelihood of delinquency and default among subprime loans (Danis and Pennington-Cross, 2005).

Mortgage brokers have played a greater role in the subprime sector during the subprime boom (Woodward, 2008; LaCour-Little, 2009). Empirical evidence on the behavior of broker-originated mortgages is scarce. LaCour-Little and Chun (1999) find that for the four types of mortgages analyzed, loans originated by a third party (including broker and correspondence) were more likely to prepay than loans originated by a lender. Alexander, Grimshaw, McQueen, and Slade (2002) find that third-party originated loans do not necessarily prepay faster but they default with greater frequency than similar retail loans. They suggest that third-party originated mortgages have higher default risk than similar retail loans because brokers are rewarded for originating a loan but not held accountable for the loan's subsequent performance.

Thus, the higher default rates reported in subprime lending may be because of risky borrowers, risky loan products, or a combination of both.

CRA Lending

The Community Reinvestment Act (CRA) of 1977 was created in response to charges that financial institutions were engaging in redlining and discrimination. The Act mandates that federally insured depository institutions help meet the credit needs of the communities in which they operate in a manner consistent with safe and sound operation (Avery, Courchane, and Zorn, 2009). Regulators assess each bank's CRA record when evaluating these institutions' applications for mergers, acquisitions, and branch openings. The performance of large institutions is measured under three categories of bank activities: lending, services, and investment, with the lending test carrying the most weight (at least 50%).[1] For the lending test, it examines the amount and proportion of lending activities made within an institution's assessment area.[2] Usually, loans are regarded as ''CRA-related'' if they are made by CRA-regulated institutions within their assessment areas to low-income borrowers (those with less than 80% area median income (AMI), regardless of neighborhood income) or in a low- income neighborhood (with less than 80% AMI, regardless of borrower income) (Avery, Bostic, and Canner, 2000).

The CRA lending test also examines the use of *innovative or flexible* lending practices to address the credit needs of LMI households and community. In response, many banks have developed ''CRA Special Lending Programs'' or have introduced mortgage products characterized by more flexible underwriting standards. Survey results suggest that most financial institutions offer these special programs, and that most of the programs relate to home mortgage lending, which typically feature some combination of special outreach, counseling and education, and underwriting flexibility (especially in terms of reduced cash to close, alternative credit verification, and higher debt-to-income thresholds) (Avery, Bostic, and Canner, 2000). Apgar and Duda (2003) and Avery, Courchane, and Zorn (2009) suggest the CRA has had a positive impact on underserved populations by enabling the origination of a higher proportion of loans to low-income borrowers and communities than they would have without CRA.

CRA-type mortgages are different from subprime loans in that CRA products usually have prime-term characteristics. In general, they are believed to carry a higher risk because they are originated by liberalizing one or two underwriting criteria. A few studies investigating the delinquency behaviors among CRA borrowers suggest the delinquency rate of CRA mortgages is comparable to that of FHA loans after excluding loans with low loan-to-value ratios (LTV) (e.g., Quercia, Stegman, Davis, and Stein, 2002). Laderman and Reid (2009) find loans originated by CRA-regulated lenders are significantly less likely to be in foreclosure than those originated (most are subprime loans) by independent mortgage companies in California. They also find that whether or not a loan was originated by a CRA lender within its assessment area is an even more important predictor of foreclosure: loans made by CRA lenders within their assessment areas are about 50% as likely to go into foreclosure as those made by independent mortgage companies. But their study focused on California only and not all the mortgages originated by CRA lenders were originated for the CRA purpose. Because of data constraints, little is known about the long-term viability of the homeownership opportunities that the CRA-related products provide.

Why Different Markets Coexist

To increase the flow of funds into low-income populations and neighborhoods, the CRA encourages lenders to meet credit needs within their service or catchment area, taking into account safety and soundness considerations. Liberalizing one or two traditional mortgage underwriting standards allows lenders to make loans to those who would otherwise not qualify for a prime mortgage (for instance, not requiring mortgage insurance when the downpayment is less than 20% makes loans more affordable for some borrowers). In this sense, both CRA and subprime products may target many of the same borrowers. In fact, recent studies suggest there is a significant overlap between borrowers holding subprime mortgages and those holding prime loans, FHA loans, and other loan products, particularly among LMI borrowers with marginal credit quality (e.g., Bocian, Ernst, and Li, 2007).

Why would many people who could qualify for low-cost prime-type loans take out subprime products? First, many borrowers, especially those with an impaired credit history, are usually financially unsophisticated and may feel they have limited options. Courchane, Surette, and Zorn (2004, p. 365) indicate that subprime borrowers ''are less knowledgeable about the mortgage process, are less likely to search for the best rates, and are less likely to be offered a choice among alternative mortgage terms and instruments.'' Especially, for some nontraditional mortgages, including interest-only mortgages, negative amortization mortgages, and mortgages with teaser rates, they were apparently not well understood by many borrowers. When borrowers do not know the best price and are less likely to search for the best rates, it is likely that they cannot make the right decision when they shop for mortgage products. In fact, Courchane, Surette, and Zorn (2004) find that search behavior, as well as adverse life events, age, and Hispanic ethnicity contribute to explaining the choice of a subprime mortgage.

Second, *predatory lending* or abusive lending practices are concentrated in the subprime sector, which may explain why some borrowers end up with certain loans. Unscrupulous lenders, or brokers as their agents, may take advantage of uninformed borrowers by charging fees and rates not reflected of the risk, by not informing borrowers of lower cost loan alternatives, and by offering products and services without full disclosure of terms and options. Renuart (2004) highlights the role of loan steering and abusive push-marketing of subprime lending practices, in which lenders steer borrowers to subprime products instead of low-cost prime alternatives. In short, borrowers generally sort to prime/CRA, subprime or other mortgage markets based on their risk profile. However, the lack of financial sophistication for some borrowers, the poor alignment of incentives, and moral hazard considerations are some of the many reasons borrowers—especially marginally qualified borrowers—may receive less desirable mortgage products than they can be qualified for.

Data and Methodology

The data for this study come from one LMI-targeted lending program, the Community Advantage Program (CAP), developed by Self-Help, a non-profit community development finance institution in North Carolina, in partnership with a group of lenders, Fannie Mae, and the Ford Foundation. Participating lenders establish their own guidelines. The most common variants from typical conventional, prime standards are: reduced cash required to close (through lower down payment and/or lower cash reserve requirements); alternative measures or lower standards of credit quality; and flexibility in assessing repayment ability (through higher debt ratios and/or flexible requirements for employment history).[3] These guidelines variants could be combined or used to offset each other.[4] Nearly 90% of the programs feature exceptions in at least two of these areas, and more than half feature exceptions in all three. The majority of programs combine neighborhood and borrower targeting.

Under the LMI-targeting CAP lending program, participating lenders are able to sell these nonconforming mortgages to Self-Help, which then securitizes and sells them to Fannie Mae or other investors. Participating lenders originate and service the loans under contract with Self-Help. It should be emphasized that, while many of the borrowers are somewhat credit impaired, the program cannot be characterized as subprime. The vast majority of CAP loans are retail originated (in contrast to broker originated) and feature terms associated with the prime market: thirty-year fixed-rate loans amortizing with prime-level interest rates, no prepayment penalties, no balloons, with escrows for taxes and insurance, documented income, and standard prime-level fees. As a LMI-targeting program, CAP has some program-specific characteristics such as income and geographic limitations.[5]

The data on subprime loans come from a proprietary database from Lender Processing Services, Inc. (LPS, formerly McDash Analytics), which provides loan information collected from approximately 15 mortgage servicers. LPS' coverage in the subprime market by volume increased from 14% in 2004 to over 30% in 2006, based on an estimation using data from Inside Mortgage Finance. There is no universally accepted definition of subprime mortgage; the three most commonly used definitions are: (1) those categorized as such by the secondary market, (2) those originated by a subprime lender as identified by HUD's annual list, and (3) those that meet HUD's definition of a ''high-cost'' mortgage (Avery, Brevoort, and Canner, 2007b; Gerardi, Shapiro, and Willen, 2007). This paper primarily follows the first definition and considers the loans with ''B'' or ''C''

Exhibit 1 | Construction of Subprime Study Sample

	# of Observations
Step 1: Subprime loans meeting the following criteria: home purchase loans, first-lien; single family house, 30-year amortization, conforming loans with a minimum loan amount of $10,000 only.	544,849
Step 2: Exclude loans with no or limited documentation or missing information for the following variables: LTV, Fico score, DTI, documentation	86,697
Step 3: Exclude loans not in ZIP Codes with CAP activities and loans without complete payment history	42,065

Notes: Based on authors' calculation from LPS. Subprime loans here include B&C loans and high-cost ARMs (with a margin greater than 300 basis points).

grade categorized by the secondary market as subprime loans.[6] High-cost ARMs are considered as subprime in this analysis. Less than 20% of loans in the LPS study sample are included solely because they are considered high-cost, defined as having a margin greater than 300 basis points (Poole, 2007). In addition, we appended to the data selected census and aggregated HMDA variables at a ZIP Code level, including the Herfindahl-Hirschman Index (''HHI'') calculated from HMDA, racial and educational distribution from census data, and area average FICO scores calculated from the LPS data.

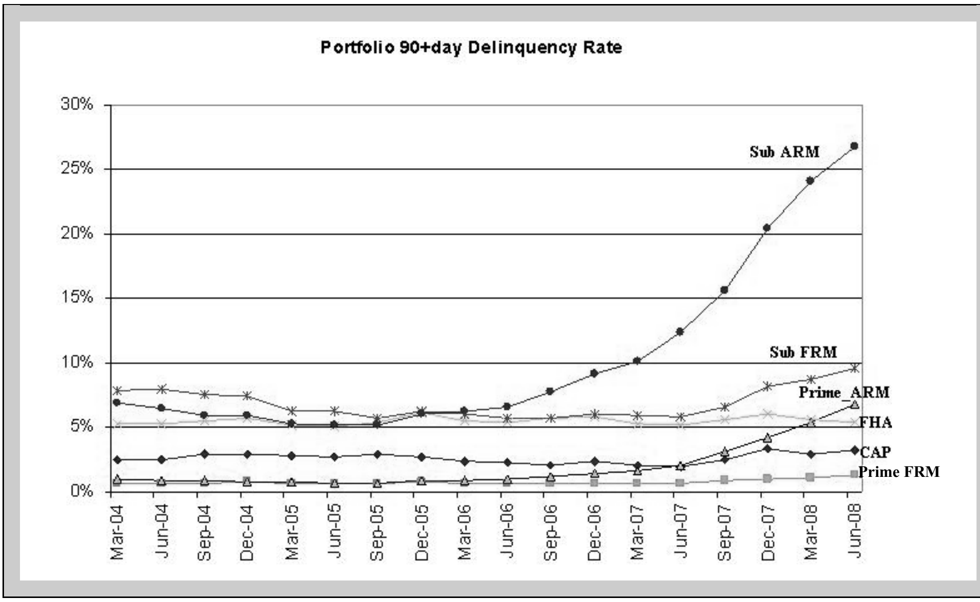
The sample of 9,221 CAP loans originated from 2003 to 2006. All are first-lien, owner-occupied, fixed-rate conforming home purchase loans with full or alternative documentation. National in scope, these loans were originated in 41 states, with about two-thirds concentrated in Ohio, North Carolina, Illinois, Georgia, and Oklahoma. To make sure the subprime loans are roughly comparable to CAP loans, as Exhibit 1 shows, the analysis is limited to subprime mortgages also characterized as first-lien, single-family, purchase-money, and conforming loans with full or alternative documentation that originated during the same period. Loans with missing values for some key underwriting variables (FICO score, LTV, DTI, and documentation status) and loans without complete payment history were eliminated. Finally, because the goal is to compare CAP and subprime loans in the same market, subprime loans in areas without CAP lending activities were excluded. Overall, the sample consists of 42,065 subprime loans. Exhibit 2 summarizes some important characteristics of both CAP loans and subprime loans in this analysis. Significance tests show that almost all variables across the two groups differ significantly before matching, indicating that the covariate distributions are different between CAP and subprime loans in the original sample. Worthy of mention is that a few seasoned loans entered the CAP and LPS datasets months after origination. But as the shares of seasoned loans that were either

Exhibit 2 | Descriptive Statistics (Mean or Percentage)

Variable	CAP	Subprime
Debt-to-income ratio*		
DTI<28%	0.126	0.163
DTI 28%–36%	0.278	0.158
DTI 36%–42%	0.315	0.178
DTI>42%	0.281	0.501
FICO score*		
<580	0.031	0.213
580–620	0.109	0.263
620–660	0.224	0.225
660–720	0.324	0.192
≥ 720	0.312	0.107
LTV*		
<80%	0.037	0.369
80%–90%	0.050	0.381
90%–97%	0.090	0.167
≥ 97%	0.823	0.083
Loan Characteristics		
*Loan_amt**	100.86	148.1
ARMs*	—	0.903
Broker*	—	0.808
Prepayment penalty*	—	0.495
Note Rate*	6.66%	7.87%
Neighborhood / Local Characteristics		
HHI index (in 10,000, 2005)*	0.051	0.036
Mean area FICO Score (2005)*	688.6	685.2
Share of minority*	0.293	0.482
Education distribution*		
Share of less high school	0.199	0.239
Share of high school	0.318	0.283
Share of some college	0.272	0.292
Share of college and above	0.211	0.186
Geography: top 5 states	OH (22.3%)	CA (19.2%)
	NC (14.6%)	TX (11.0%)
	IL (12.6%)	FL (10.1%)
	GA (11.4%)	IL (9.1%)
	OK (5.8%)	GA (5.3%)
Origination Year		
2003	2,670	4,680
2004	2,581	18,380
2005	2,251	11,703
2006	1,719	7,302
N	9,221	42,065

Note:
*Bivariate χ^2 test or *t*-test significant at the 0.01 level.

Exhibit 3 | 90-day Delinquency Rate by Loan Types



Source: Mortgage Banker Association (2008) and Self-Help.

marginal or similar for CAP and subprime loans was verified, this does not appear to cause serious bias for the empirical results.[7]

Though drawn from similar markets, the CAP borrowers (including all active loans originated as early as 1990s) are not experiencing the same mortgage woes as subprime borrowers. As Exhibit 3 shows, 3.21% of the sample of community lending borrowers were 90-days' delinquent or in foreclosure process in the second quarter of 2008. This was slightly higher than the 2.35% delinquency rate on prime loans but well below the 17.8% on subprime loans nationwide. Especially, over 27% of subprime ARMs were in foreclosure or serious delinquency, which was almost nine times that of community lending loans.

In summary, the CAP and subprime samples have identical characteristics for the following important underwriting variables: lien status, amortization period, loan purpose, occupancy status, and documentation type. They were originated during the same time period and roughly in the same geographic areas. However, the two samples differ in other underwriting factors, including DTI, LTV, and FICO score, and in loan amount and some loan features that are more common only for subprime loans.

Methodology

The PSM method has been widely used to reduce selection biases in recent program evaluation studies. PSM was first developed by Rosenbaum and Rubin (1983) as an effort to more rigorously estimate causal effects from observational data. Basically, PSM accounts for observable heterogeneity by pairing participants with nonparticipants on the basis of the conditional probability of participation, given the observable characteristics. The PSM approach has gained increasing popularity among researchers from a variety of disciplines, including biomedical research, epidemiology, education, sociology, psychology, and social welfare (see review in Guo, Barth, and Gibons, 2006).

There are three basic steps involved in implementing PSM. First, a set of covariates is used to estimate the propensity scores using *probit* or *logit*, and the predicted values are retrieved. Then each participant is paired with a comparable nonparticipant based on propensity scores. In the last step, regression models or other methods can be applied to the matched group to compare the outcomes of participants and nonparticipants.

In this case, because receiving a subprime loan is a choice/assignment process rather than randomly assigned, the PSM method is used to adjust this selection bias. In the first step, logistic regression models are employed to predict the propensity ($e(x_i)$) for borrower i ($i = 1,...,N$) to receive a subprime loan ($S_i = 1$) using a set of conditioning variables (x_i):

$$e(x_i) = pr(S_i = 1|X_i = x_i). \tag{1}$$

In the second step, the nearest-neighbor with caliper method is used to match CAP borrowers with borrowers holding subprime loans based on the estimated propensity scores from the first step. The method of nearest-neighbor with caliper is a combination of two approaches: traditional nearest-neighbor matching and caliper matching.[8] This method begins with a random sort of the participants and nonparticipants. The first participant is selected and then the nonparticipant subject with the closest propensity score within a predetermined common-support region called caliper (δ) is determined. The approach imposes a tolerance level on the distance between the propensity score of participant i and that of nonparticipant j. Formally, assuming $c(p_i)$ as the set of the neighbors of i in the comparison group, the corresponding neighborhood can be stated as follows.

$$c(p_i) = \{j|\delta > \|p_i - p_j\|\}. \tag{2}$$

If there is no member of the comparison group within the caliper for the treated unit i, then the participant is left unmatched and dropped from the analysis. Thus, caliper is a way of imposing a common support restriction. Naturally, there is uncertainty about the choice of a tolerance level since a wider caliper can increase the matching rate but it also increases the likelihood of producing inexact matching. A more restrictive caliper increases the accuracy but may significantly reduce the size of the matched sample.

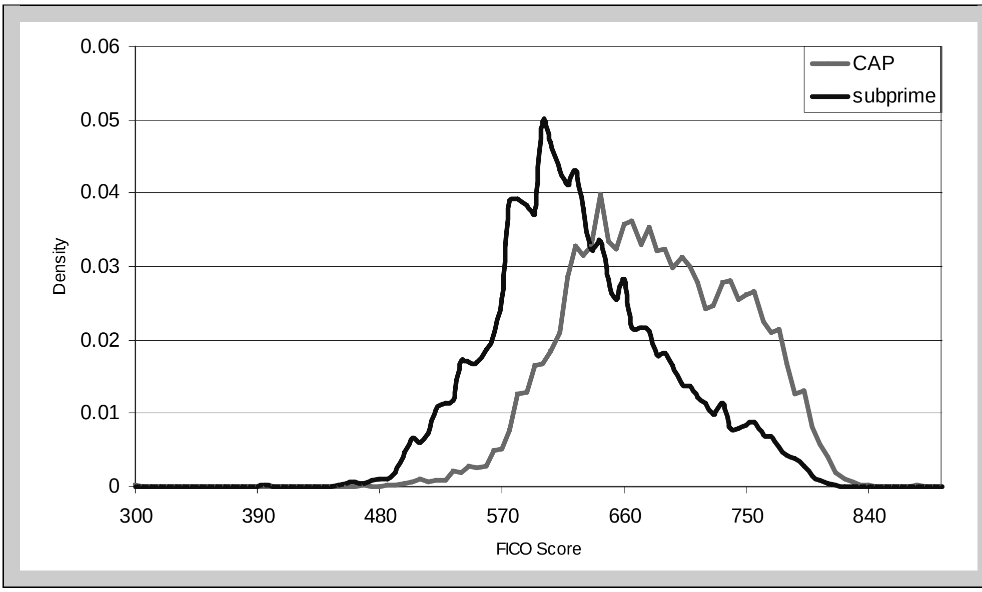
In the context of observational studies, the PSM methods seek to mimic conditions similar to an experiment so that the assessment of the impact of the program can be based on a comparison of outcomes for a group of participants (i.e., those with $S_i = 1$) with those drawn from a comparison group of non-participants ($S_i = 0$). The observational data need to be checked to see if they meet the two primary assumptions underlying the PSM methods: the *conditional independence* assumption[9] and the *overlap* assumption.

The conditional independence assumption states that conditional on observable characteristics, participation (receiving subprime here) is independent of potential outcomes and unobservable heterogeneity is assumed to play no role in participation (Dehejia and Sadek, 2002). In other words, assuming that there are no unobservable differences between the two groups after conditioning on observed characteristics, any systematic differences in outcomes between participants and nonparticipants are due to participation. Of course, it is possible that lenders have access to more information about the borrower and local market than the information in the dataset and the unobservable lender information may influence the estimation results. The strategy is to use a well-specified logit regression to estimate the probability of taking out a subprime mortgage for each cohort, grounded on a sound understanding of the subprime market. The second assumption, the overlap assumption, is that there must be individuals in the comparison group with the same or similar propensity as the participant of interest in order for the matching to be feasible, In this case, it is highly likely that there is significant overlap between the CRA-type CAP loans and the subprime sample since both of them focus on households with marginal credit quality and have identical loan characteristics, such as lien status, loan purpose, occupancy status, and documentation type. As shown in Exhibit 4, the distribution of credit scores for the CAP and subprime borrowers, subprime borrowers tend to have lower FICO scores than CAP borrowers, but there is a significant overlap in these distributions.

In the third step, a multinomial regression model (MNL) is used to further control factors that may influence the performance of the new sample after loan origination, many of which are time-varying. In each month the loan can be in only one state or outcome (active, default, or prepaid). Since the sum of the probabilities of each outcome must equal to one, the increase in the probability of one outcome necessitates a decrease in the probability of at least one competing outcome. Thus the multinomial logit model is a competing risk model. The mortgage borrowers have three options each month:

- **Default**: This study treats the incidence of the first 90-day delinquency as a proxy of default.

Exhibit 4 | CAP and Subprime FICO Score Distribution (2003–2006)



Source: Lender Processing Services, Inc. (LPS) and Self-Help.

- **Prepaid**: If a loan was prepaid before it is seriously delinquent, it is considered a prepayment.
- **Active**: Active and not default (not seriously delinquent in some models)

The probability of observing a particular loan outcome is given by:

$$\Pr(y_{it} = j) = \frac{e^{\beta_j Z_{it} + \gamma_j S_i}}{1 + \sum_{k=1}^{2} e^{\beta_k Z_{it} + \gamma_k S_i}} \; for\ j = 1,2$$

$$\Pr(y_{it} = j) = \frac{1}{1 + \sum_{k=1}^{2} e^{\beta_k Z_{it} + \gamma_k S_i}} \; for\ j = 0 \qquad (3)$$

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

where $j = 0,1,2$ represents the three possible outcomes of a loan and the omitted category ($j = 0$) remains active and not seriously delinquent (*Active*); d_{ijt} is an indicator variable taking on the value 1 if outcome j occurs to loan i at time t, and zero otherwise; Z contains a set of explanatory variables; and β is the coefficient. To identify the difference between the performance of CAP loans and subprime loans, S contains a subprime dummy variable or indicators of subprime loan characteristics.

Specifically, the impact one origination channel and two loan characteristics is examined: the prepayment penalty, the adjustable rate, and the broker origination channel. Six mutually exclusive dummy variables are constructed for the combinations of these three characteristics,[10] such as *sub_bro&arm&ppp* for "broker-originated subprime loans with adjustable rates and prepayment penalties" and *sub_arm* for "retail-originated subprime loans with adjustable interest rates and no prepayment penalties." None of the CAP loans have these features, and they are set as the reference group in both models.[11]

Empirical Analysis

Propensity Score Matching

Several empirical studies suggest that borrowers take out subprime mortgages based on their credit score, income, payment history, level of down payment, debt ratios, and loan size limits; there is mixed evidence on the effect of demographics (Courchane, Surette, and Zorn, 2004; Cutts and Van Order, 2005; Chomsisengphet and Pennington-Cross, 2006; Courchane, 2007). Based on the literature review, two key underwriting factors of FICO score and DTI are included in the analysis. They are assumed to directly affect credit risk and therefore affect mortgage choice/assignment, since higher credit risk is hypothesized to be associated with a greater probability of taking out a subprime mortgage. *LTV*, another important underwriting variable, is generally considered to raise endogeniety concerns. In this case, higher *LTV* is one distinct characteristic of most CAP loans, with over 82% of CAP loans having an *LTV* equal to or higher than 97%. By contrast, most subprime loans have an *LTV* of less than 90%. Courchane, Surette, and Zorn (2004) also suggest that high LTV may be associated with higher risk but is not necessarily associated with getting a subprime mortgage. Because the focus here is the impact of borrower and neighborhood characteristics on borrowers' choice /assignment of mortgages, LTV variables are not included in the model.

In addition to the underwriting variables, loan amount is included, along with several factors measuring local market dynamics and credit risk. A ZIP Code level credit risk measure was constructed: the mean FICO score for mortgages originated in the preceding year from the LPS data. The hypothesis is that subprime lenders tend to market in neighborhoods or areas with a larger share of potential borrowers who have impaired credit history. The ZIP Code level educational distribution and the share of minority in the ZIP Code from the 2000 Census were included in the models. The ZIP Code educational distribution was included as a proxy of residents' financial knowledge and literacy. Furthermore a ZIP Code level HHI was constructed using HMDA data to measure the extent of competition in the market in which borrowers' properties are located.[12] The HHI measure also partially represents the volume of transactions in the area, since more transactions in a hot market could, though not necessarily would, attract more lenders to the market. In addition, quarterly calendar dummy variables were included to account for fluctuations in the yield curve that could affect market dynamics.

Exhibit 5 presents the results from logistic regression models for different vintages. Across different years, credit risk measures are highly predictive: borrower FICO score, coded into buckets with above 720 as the holdout category, is highly predictive of the use of subprime loans; coefficients are relatively large and decrease monotonically as credit score categories increase. In other words, as expected, the higher the FICO score, the lower the probability of taking out a subprime mortgage. Compared to those with very high DTI (>42%), borrowers with lower DTIs are generally less likely to receive subprime loans; exceptions are the buckets with low DTI (<28%) for the 2005 and 2006 samples. While it seems CAP borrowers had very high DTIs in 2006, the results generally suggest that borrowers with very high DTIs are more likely to receive subprime loans. In all the models, loan amount is positive for the use of subprime loans, consistent with the hypothesis that subprime borrowing involves higher costs, with costs being driven by large fixed components.

Further, ZIP Code level average credit score is statistically significant and negatively related to the probability of taking out a subprime mortgage, suggesting that borrowers in areas with a higher share of low-score population are more likely to receive subprime loans. ZIP Code level education performs about as expected, with higher educational attainment roughly associated with a reduced probability of receiving a subprime mortgage. Borrowers in areas with a higher share of minorities are more likely to use subprime mortgages. Finally, higher HHIs are associated with a lower probability of taking out a subprime mortgage, suggesting that, at least in the period from 2003 to 2006, subprime loans were more likely to be in the markets with more intensive competition and/or more transactions.

In this analysis, the logit is defined rather than the predicted probability as the propensity score, because the logit is approximately normally distributed. For the one-to-one nearest neighbor with caliper match, the subprime loan with the closest propensity score within a caliper was selected for the first CAP loan after the subprime and randomly ordered CAP loans. Both cases were then removed from further consideration and the subprime loan was selected to match the next CAP loan. For the one-to-many match, the subprime loans were matched with CAP loans with the closest propensity score within a caliper after all the loans were randomly sorted. Instead of removing the matched cases after matching, as in the one-to-one match, the matched CAP loans were kept in the sample to find the matching CAP loans for the next subprime loan. This allows us to match as many subprime loans as possible for each CAP loan. Two different calipers, 0.1 and

Exhibit 5 | Logistic Regression Models Predicting Propensity Scores

	2003		2004		2005		2006	
Variable	Coeff.	*P*-Value	Coeff.	*P*-Value	Coeff.	*P*-Value	Coeff.	*P*-Value
dti<28	−0.172	0.088	0.006	0.941	0.616	0.000	1.324	0.000
dti 28–36	−1.369	0.000	−1.252	0.000	−0.603	0.000	0.216	0.018
dti 36–42	−1.411	0.000	−1.486	0.000	−0.837	0.000	−0.160	0.060
dti>42								
cscore<580	4.632	0.000	3.943	0.000	4.182	0.000	1.900	0.000
cscore 580–620	2.040	0.000	2.237	0.000	2.846	0.000	1.245	0.000
cscore 620–660	1.431	0.000	1.121	0.000	1.438	0.000	1.021	0.000
cscore 660–720	0.850	0.000	0.550	0.000	0.632	0.000	0.483	0.000
cscore ≥ *720*								
loan_amt	0.012	0.000	0.013	0.000	0.011	0.000	0.010	0.000
qtr1	0.055	0.585	−0.553	0.000	0.606	0.000	1.137	0.000
qtr2	−0.019	0.843	−0.062	0.407	0.315	0.000	0.891	0.000
qtr3	−0.545	0.000	0.070	0.342	0.073	0.372	0.601	0.000
qtr4								

Exhibit 5 | (continued)

Logistic Regression Models Predicting Propensity Scores

Variable	2003 Coeff.	2003 *P*-Value	2004 Coeff.	2004 *P*-Value	2005 Coeff.	2005 *P*-Value	2006 Coeff.	2006 *P*-Value
HHI (in 10,000)	−14.763	0.000	−18.747	0.000	−21.058	0.000	−23.296	0.000
area credit score	−0.004	0.046	−0.004	0.053	−0.002	0.438	0.000	0.937
pctmin	−0.007	0.001	0.006	0.001	0.017	0.000	0.014	0.000
pct_less_high								
pct_high	−0.124	0.000	−0.077	0.000	−0.057	0.000	−0.144	0.000
pct_somecoll	0.062	0.000	0.049	0.000	0.054	0.000	0.015	0.037
pct_coll	−0.082	0.000	−0.067	0.000	−0.058	0.000	−0.092	0.000
_cons	6.015	0.000	5.411	0.000	2.164	0.177	6.127	0.001
Pseudo R^2	0.42		0.36		0.38		0.35	

Notes: For 2003, *N* = 7,350; for 2004, *N* = 20,961; for 2005, *N* = 13,954; and for 2006, *N* = 9,021.

Exhibit 6 | Description of Matching Schemes and Resample Sizes

		N of Original Sample	N of the New Sample	
Scheme	Description of matching method	CAP	CAP	Subprime
Match 1	Nearest 1-to-1 using caliper = 0.1	9,221	5,558	5,558
Match 2	Nearest 1-to-1 using caliper = 0.25	9,221	6,349	6,349
Match 3	Nearest 1-to-many using caliper = 0.1	9,221	3,943	35,971
Match 4	Nearest 1-to-many using caliper = 0.25	9,221	3,944	36,236

Notes: For the one-to-one nearest neighbor with caliper match, the subprime loan with the closest propensity score within a caliper for the first CAP loan was selected after the sample was randomly ordered. Both cases were removed from further consideration. The subprime loan was selected to match the next CAP loan. For the one-to-many match, subprime loans were matched with CAP loans with the closest propensity score within a caliper after all the loans were randomly sorted. Instead of removing the matched cases after matching as in the one-to-one match, the matched CAP loans were kept in the sample and matched to the matching CAP loan for the next subprime loan.

0.25 times of standard error were evaluated, as suggested by Rosenbaum and Rubin (1985). In other words, two matching algorithms were employed, which allowed matching one CAP loan with one or multiple subprime loans, and two caliper sizes, allowed evaluation of the sensitivity of the findings to varying sizes. For the one-to-many matched sample, to ensure that the analysis was representative of the matched set, we applied a system of weights, where the weight was the inverse of the number of subprime loans that matched to one single CAP loan.

Exhibit 6 describes the four matching schemes and numbers of loans for the resamples: Match 1 and Match 2 are based on the one-to-one match; Match 3 and Match 4 are based on the one-to-many match. Match 1 and Match 3 use nearest neighbor matching within a more restrictive caliper of 0.1, while other matching schemes employ a wider caliper (0.25 times of the standard deviation of the propensity scores). The results show that the more restrictive caliper does not dramatically reduce the sample size; about 791 cases (12%) were lost from Match 2 to Match 1 and only one CAP loan from Match 4 to Match 3. Because the qualitative results do not change and a restrictive caliper can lower the likelihood of producing inexact matching, the schemes using the more restrictive caliper size of 0.1 (Matches 1 and 3) were the focus of the analysis of loan performance. For the one-to-one match (Match 1), the sample included 5,558 CAP loans and 5,558 matching subprime loans. For the one-to-many match, the sample was 35,971 subprime loans matched to 3,943 CAP loans (Match 3).

Covariate distributions were checked after matching. Both Match 1 and Match 3 removed all significant differences, except LTV variables, between groups. For the matched groups, as Exhibit 7 shows, borrowers are remarkably similar across all groups except for LTV ratios, and there was a reduced but more balanced sample of CAP and subprime borrowers. Compared to CAP loans, which are usually fixed-rate retail loans with no prepayment penalty, subprime loans have distinctive features and terms. A vast majority (86%) of subprime loans are adjustable rate mortgages; most (70%) were obtained through brokers; and many (41%) have prepayment penalties.

Performance of the Matched Sample

The performance of CAP loans and subprime loans with similar characteristics is examined next using a very rich panel dataset (loan-months). For the matched sample, the payment history during the period from loan origination to March 2008 is evaluated. During this period, CAP loans had a lower serious delinquency rate: only 9.0% had ever experienced 90-day delinquencies before March 2008, compared to 19.8% of comparable subprime loans (Exhibit 8). Subprime loans also had a higher prepayment rate: 38% compared to about 18% for the matched CAP loans.

In addition to the subprime variables, the MNL model included important underwriting variables, including borrower DTI ratio, credit history, loan age, and loan amount, as well as the put option. According to the option-based theory, home equity plays a central role in determining the probability of foreclosure (Deng, Quigley, and Van Order, 2000). The value of the put option is proxied by the ratio of negative equity to the estimated property value.[13] Relying on the unpaid balance of the first-liens in the calculation of the put option likely overestimates the risk of subprime loans since, as suggested in Zelman, McGill, Speer, and Ratner (2007), some subprime loans may have second mortgages that were not captured here. A separate model was run that assumed all subprime loans with LTVs in the 75%–95% range have a combined LTV of 95% at origination. The findings reveal that the estimated cumulative default rates of subprime loans are still significantly higher than that of CAP loans but the magnitude becomes smaller.[14]

Falling interest rates may lead to faster prepayments and drive down delinquency rates as borrowers refinance their way out of potential problems. To capture the change in interest rate environment, the difference between the prevailing interest rates was employed, which is proxied by the average interest rate of 30-year fixed-rate mortgages from the Freddie Mac Primary Mortgage Market Survey (PMMS), and the prevailing interest rates at the time of loan origination.

Consistent with prior work, the matched sample was further separated into two cohorts based on years of origination. Subprime loans that originated in 2003 and 2004 were underwritten during a time of historically low interest rates and a strong

Exhibit 7 | Significance Tests of the Resamples

	Match 1		Match 3	
Variable	CAP	Subprime	CAP	Subprime
Debt-to-Income Ratio				
DTI<28%	0.229	0.221	0.223	0.218
DTI 28%–36%	0.261	0.249	0.242	0.233
DTI 36%–42%	0.375	0.391	0.397	0.403
DTI>42%	0.135	0.139	0.138	0.146
FICO Score				
<580	0.047	0.049	0.165	0.164
580–620	0.150	0.155	0.251	0.241
620–660	0.256	0.241	0.296	0.292
660–720	0.305	0.305	0.165	0.164
≥ 720	0.242	0.250	0.123	0.139
LTV (* for Match 1)				
<80%	0.042	0.314	0.044	0.305
80%–90%	0.062	0.276	0.066	0.282
90%–97%	0.110	0.209	0.117	0.208
≥ 97%	0.786	0.201	0.773	0.204
Loan Characteristics				
*loan_amt**	109.4	109.7	112.0	113.2
ARMs*		0.864		0.880
Broker*		0.696		0.682
Prepayment penalty*		0.413		0.422
Note Rate*	0.066	0.078	0.066	0.078
N	5,558	5,558	3,943	35,971**

Note:
*Bivariate χ^2 test or *t*-test significant at 0.01 level.
**Statistics based on Match 3 are weighted average and the weight is the inverse of number of subprime loans that matched to one CAP loan.

economy, leading to a relatively good performance with very low default rates (Cutts and Merrill, 2008). Many borrowers were able to refinance their mortgages or sell their houses because of lax underwriting and high house price appreciation before 2007, which extinguished the default option. Instead, subprime loans that originated in 2005 and 2006, especially subprime ARMs, have not performed as well. These two cohorts capture some unobservable heterogeneity characterizing mortgages that originated in a booming housing market and those that originated in a softening housing market.

The results from the MNL regressions based on different matching samples are listed in Exhibit 9 (one-to-one match) and Exhibit 10 (one-to-many match). Model

Exhibit 8 | Performance Measures of the New Samples

	Whole Sample		2003–2004 Sample		2005–2006 Sample	
	% of 90-Day	% Prepayment	% of 90-Day	% Prepayment	% of 90-Day	% Prepayment
CAP	8.98	18.46	7.64	25.73	10.94	7.84
Subprime	19.81	38.27	12.97	50.06	29.81	21.04
N	11,116		6,600		4,516	

Note: Observation period is from origination to March 2008; if a loan was 90-day delinquent and then prepaid, it is considered as a 90-day delinquency only.

1 considers the subprime dummy variable only, while Model 2 helps explain the difference in performance between CAP and subprime loans. The results based on samples using varying algorithms are quite consistent, so Exhibit 10 only lists results for the subprime variables. It is not easy to interpret the results based on the coefficients from the MNL regressions directly. The cumulative default and prepayment rates were estimated for the first 24 months after origination for borrowers with impaired credit score (FICO score 580–620) and with mean value of other regressors, except loan age and loan characteristics, based on the MNL regression results.

Summary of Findings

First, there is consistent evidence that subprime loans have a higher default risk and a higher prepayment probability than CAP loans (Exhibit 11). The estimated cumulative default rate for a 2004 subprime loan is 16.8%, about four times that of CAP loans (4.2%). For a 2006 subprime loan, the cumulative default rate is 47.5%, about 3.3 times that of comparable CAP loans (14.3%). In other words, CAP loans were about 70% *less* likely to default than a comparable subprime loan across different vintages. The default rate of the 2005–2006 cohort is significantly higher than that of the 2003–2004 cohort for loans with same loan features. Very likely this is because of changes in the underwriting standard and in economic conditions, as well as other unobservable heterogeneity.

Subprime loans with adjustable rates are found to have a significantly higher default rate than comparable CAP loans. And when the adjustable rate term is combined with the prepayment-penalty feature, the default risk of subprime loans becomes even higher. For a 2004 *sub_arm* loan (retail-originated subprime ARM without prepayment penalty), the estimated cumulative default rate is 6.6%, slightly higher than that of CAP loans (4.2%). But if the adjustable rate subprime

Exhibit 9 | MNL Regression Results of Default and Prepayment (Match 1 in Exhibit 6)

		2003–2004 Sample				2005–2006 Sample			
		Model 1		Model 2		Model 1		Model 2	
	Variable	Coeff.	P > z	Coeff.	P > z	Coeff.	P > z	Coeff.	P > z
Default	*put*	0.041	0.000	0.044	0.000	0.050	0.000	0.052	0.000
	dti 28–36	0.580	0.000	0.582	0.000	0.086	0.517	0.096	0.467
	dti 36–42	0.631	0.000	0.597	0.000	0.032	0.807	0.024	0.853
	dti>42	0.323	0.029	0.519	0.000	−0.238	0.068	0.019	0.884
	cscore <580	2.410	0.000	2.195	0.000	1.688	0.000	1.481	0.000
	cscore 580–620	1.989	0.000	1.791	0.000	1.283	0.000	1.061	0.000
	cscore 620–660	1.468	0.000	1.286	0.000	1.036	0.000	0.909	0.000
	cscore 660–720	0.633	0.000	0.513	0.001	0.452	0.004	0.390	0.010
	unpaid balance (in log)	−0.353	0.000	−0.261	0.009	−0.168	0.071	−0.069	0.461
	loan age (in log mon)	0.937	0.000	1.006	0.000	1.005	0.000	1.056	0.000
	area credit score	−0.010	0.000	−0.009	0.000	−0.012	0.000	−0.010	0.000
	rate difference	−0.105	0.286	−0.108	0.272	−0.044	0.672	−0.058	0.576
	area unemp rate	0.047	0.091	0.049	0.077	0.040	0.169	0.020	0.484
	y2003 (y2005)	−0.038	0.676	−0.108	0.242	−0.603	0.000	−0.496	0.000
	subprime	1.589	0.000			1.604	0.000		
	sub_arm			0.541	0.003			0.363	0.032
	sub_arm&ppp			1.530	0.029			1.906	0.000
	sub_bro			1.944	0.000			1.450	0.000
	sub_bro&ppp			1.983	0.000			1.528	0.000
	sub_bro&arm			1.652	0.000			1.906	0.000
	sub_bro&arm&ppp			1.985	0.000			1.827	0.000
	Constant	0.871	0.517	−0.908	0.507	1.653	0.231	−0.912	0.512

Exhibit 9 | (continued)

MNL Regression Results of Default and Prepayment (Match 1 in Exhibit 6)

		2003–2004 Sample				2005–2006 Sample			
		Model 1		Model 2		Model 1		Model 2	
	Variable	Coeff.	P > z	Coeff.	P > z	Coeff.	P > z	Coeff.	P > z
Prepay	*put*	−0.015	0.000	−0.014	0.000	−0.007	0.064	−0.006	0.186
	dti 28–36	0.290	0.000	0.303	0.000	−0.045	0.761	0.016	0.916
	dti 36–42	0.350	0.000	0.356	0.000	0.059	0.682	0.149	0.312
	dti>42	0.014	0.836	0.118	0.091	−0.301	0.029	−0.174	0.249
	cscore<580	0.145	0.311	0.006	0.969	−0.087	0.673	−0.010	0.963
	cscore 580–620	0.083	0.309	−0.003	0.972	0.239	0.065	0.276	0.044
	cscore 620–660	0.331	0.000	0.270	0.000	−0.192	0.132	−0.139	0.287
	cscore 660–720	0.153	0.004	0.143	0.007	−0.076	0.523	−0.115	0.343
	unpaid balance (in log)	0.329	0.000	0.298	0.000	−0.055	0.537	−0.116	0.205
	loan age (in log mon)	0.451	0.000	0.504	0.000	0.690	0.000	0.693	0.000
	area credit score	0.001	0.388	0.002	0.094	0.007	0.001	0.008	0.001
	rate difference	0.161	0.003	0.150	0.005	−0.053	0.669	−0.067	0.594
	area unemp rate	−0.014	0.399	−0.020	0.220	−0.031	0.379	−0.033	0.354
	y2003 (y2005)	−0.014	0.757	0.037	0.414	0.253	0.037	0.283	0.027
	subprime	0.922	0.000			1.239	0.000		
	sub_arm			0.612	0.000			1.130	0.000
	sub_arm&ppp			1.685	0.000			2.293	0.000
	sub_bro			0.433	0.000			1.205	0.001
	sub_bro&ppp			0.978	0.000			−0.240	0.513
	sub_bro&arm			1.083	0.000			1.663	0.000
	sub_bro&arm&ppp			1.334	0.000			0.949	0.000
	Constant	−11.201	0.000	−11.577	0.000	−11.792	0.000	−11.403	0.000

Exhibit 9 | (continued)

MNL Regression Results of Default and Prepayment (Match 1 in Exhibit 6)

Note: sub_arm represents subprime retail originated ARMs without prepayment penalty; *sub_arm&ppp* represents subprime retail originated ARMs with prepayment penalties; *sub_bro* represents subprime broker originated fixed-rate mortgages without prepayment penalties; *sub_bro&ppp* represents subprime broker originated fixed-rate mortgages with prepayment penalties; *sub_bro&arm* represents subprime broker originated ARMs without prepayment penalties; *sub_bro&arm&ppp* represents subprime broker originated ARMs with prepayment penalties. In the 2003–2004 sample, $N = 192{,}179$ of 6,600 loans Log likelihood $= -16{,}682.3$ in Model 2. In the 2005–2006 sample, $N = 93{,}646$ of 4,516 loans.

Exhibit 10 | MNL Regression Results of Default and Prepayment (Match 3 in Exhibit 6)

		2003–2004 Sample				2005–2006 Sample			
		Model 1		Model 2		Model 1		Model 2	
	Variable	Coeff.	P > z	Coeff.	P > z	Coeff.	P > z	Coeff.	P > z
Default	*subprime*	1.443	0.000			1.592	0.000		
	sub_arm			0.480	0.003			0.304	0.006
	sub_arm&ppp			1.643	0.000			2.244	0.000
	sub_bro			1.713	0.000			1.620	0.000
	sub_bro&ppp			1.775	0.000			1.773	0.000
	sub_bro&arm			1.627	0.000			1.728	0.000
	sub_bro&arm&ppp			1.843	0.000			1.951	0.000
Prepay	*subprime*	0.941	0.000			1.018	0.000		
	sub_arm			0.668	0.000			0.769	0.000
	sub_arm&ppp			1.537	0.000			1.729	0.000
	sub_bro			0.513	0.000			0.616	0.000
	sub_bro&ppp			0.897	0.000			0.608	0.000
	sub_bro&arm			1.055	0.000			1.186	0.000
	sub_bro&arm&ppp			1.380	0.000			1.234	0.000

Note: see note in Exhibit 9 for the definition of different loan products. There should be 8 dummies for different combinations of loan features but the sample sizes of the buckets of retail-originated fixed-rate subprime with and without prepayments are too small, which does not allow us conduct meaningful analysis. In the 2003–2004 sample, N = 341,367 of 16,604 loans; log likelihood = −47,494.0 in Model 1 and −47,212.4 in Model 2. In the 2005–2006 sample, N = 528,292 of 23,310 loans; log likelihood = −78,994.5 in Model 1 and −78,395.2 in Model 2.

Exhibit 11 | Estimated Cumulative Default and Prepayment Rate
(24 months after origination for a borrower with impaired credit score of 580–620)

	2004 Origination			2006 Origination		
	Default	Prepayment	Ratio to CAP (default)	Default	Prepayment	Ratio to CAP (default)
CAP	4.17%	11.58%		14.30%	7.58%	
Subprime	16.80%	25.00%	4.0	47.47%	18.82%	3.3
sub_arm	6.59%	18.14%	1.6	16.82%	21.54%	1.2
sub_arm&ppp	13.34%	42.51%	3.2	42.46%	42.03%	3.0
sub_bro	24.33%	14.10%	5.8	40.57%	19.69%	2.8
sub_bro&ppp	23.46%	22.93%	5.6	47.87%	4.99%	3.3
sub_bro&arm	17.27%	25.95%	4.1	50.71%	25.85%	3.5
sub_bro&arm&ppp	21.93%	30.99%	5.3	53.87%	14.17%	3.8

Note: see note in Exhibit 9 for the definition of different loan products. The predicted cumulative default and prepayment rate is as of 24 months after origination for a borrower with a FICO score between 580–620 and holding a mortgage originated in 2004 or 2006, with the mean value of other regressors. The estimation is based on regression results in Exhibit 9.

mortgage has a prepayment penalty, the estimated default rate increases to 13.3% for a 2004 *sub_arm&ppp* loan (retail-originated adjustable-rate subprime loan with prepayment penalty), over 100% relatively higher than that of *sub_arm*.

Finally, the broker-origination channel is significantly associated with an increased level of default. For example, the estimated cumulative default rate for a 2004 *sub_bro&arm* loan (broker-originated adjustable-rate subprime loan without prepayment penalty) is 17.3%, significantly higher than the 6.5% of the *sub_arm* loans. For a 2006 *sub_bro&arm* loan, the estimated cumulative default rate is as high as 50.7%, much higher than the 16.8% of the *sub_arm* loans. The same pattern can also be identified for adjustable-rate subprime loans with prepayment penalties. When a broker-originated subprime ARM has the term of prepayment penalty, the default risk for 2004 originations is 5.3 times as high as that of CAP loans (21.9% vs. 4.2%) and for 2006 originations 3.8 times as high (53.9% vs. 14.3%).

Overall, the results suggest that, all other observed characteristics being equal, borrowers receiving subprime loans are about three to five times more likely to default, depending on the mortgage origination year and the combined LTV. Especially, borrowers are about three to over five times more likely to default if they obtained their mortgages through brokers. When this feature is combined with the adjustable rate and/or prepayment penalty, the default risk is even higher. One possible explanation is that, as suggested in Woodward (2008) and LaCour-Little (2009), loans originated through brokers have significantly higher closing costs and prices, which increases borrowers' costs and can lead to elevated default risk. It is also possible that borrowers obtaining loans through brokers are more likely to receive products with features that may increase the default risk. Finally, it is very likely that the broker-originated loans have looser underwriting standards that have not been fully captured by the model. All these contentions are consistent with the results, and additional research is needed to examine this issue in more detail.

As to the outcome of prepayment, there are two obvious trends. The first is that subprime loans, especially subprime ARMs, have a significantly higher prepayment rate than CAP loans (Exhibit 11). Second, for recent originations (2005–2006), subprime loans with prepayment penalties are less likely to prepay than loans with similar terms but without prepayment penalties. But for early originations (2003–2004), the pattern is reversed: subprime loans with prepayment penalties have a higher prepayment rate, probably because they are more likely to be prepaid after the prepayment penalty period has expired. Although the prepayment penalty clauses for all subprime loans could not be determined because of missing values, for those loans with complete information, prepayment penalties were most frequently levied within the first two to three years of loan origination. As of March 2008, then, most prepayment penalties for 2003–2004 originations had expired. But prepayment may also be part of the problem if the borrower prepaid the loans by refinancing into another subprime product.

Empirical Results of Other Controls

Because the results for most of the variables are generally consistent across different models, discussion of other control variables is based primarily on Model 1, as summarized in Exhibit 9. For other controlled variables, the results suggest:

- **Put Option**: Borrowers with less or negative equity in their homes (larger value of *put*) are more likely to default and less likely to prepay. The results confirm the common wisdom that the level of equity in a home is a strong predictor for prepayment and default.

- **Credit History**: As expected, there is consistent evidence that borrowers with lower credit scores are more likely to experience serious delinquency.[15]

- **Debt-to-Income Ratio**: Higher debt-to-income ratios are associated with a higher default risk for the 2003–2004 cohort, but the coefficients are insignificant for the 2005–2006 sample.

Loan Characteristics:

- **Size of Unpaid Balance**: Larger loan size is generally associated with lower default risk. Larger loan size is also associated with higher prepayment probability for the 2003–2004 cohort.

Area and Neighborhood Controls:

- **Area Credit Risk**: Average credit score in the ZIP Code is significantly and negatively associated with default risk. There is also some evidence that ZIP Code average credit score is positively associated with prepayment probability (for the 2005–2006 vintage).
- **Interest Rate Dynamics**: For different cohorts, the impact of interest rate environment is different. For the 2003–2004 cohort, a larger difference between the prevailing interest rate and the average rate at loan origination increases the prepayment probability but for the recent cohort, the increase in average interest rate had no significant impact on both the prepayment and default probability.
- **County Unemployment Rate**: Average county unemployment rate is generally insignificant in explaining the default and prepayment behaviors across different models possibly because the study period ends in early 2008 when the economy-wide crisis was in its early stages.

Time Dummies:

- **Dummies of 2003 and 2005 Originations**: The 2005 originations are significantly less likely to default, compared to the 2006 cohort.

Conclusion

As the current economic crisis continues, the debate persists as to what caused the initial foreclosure crisis in the mortgage markets and what we should do in the future. The findings reveal that, for comparable borrowers, the estimated default risk is much lower with a CRA-type CAP loan than with a subprime mortgage. More narrowly, the broker-origination channel, an adjustable rate, and a prepayment penalty, all contribute substantially to the elevated risk of default among subprime loans. In the worst scenario, when broker origination is combined with the features of adjustable rate and prepayment penalty, the default risk of a borrower is about three to five times as high as that of a comparable borrower holding a CRA-type product. The results clearly suggest that the relative higher default risk of subprime loans may not be solely attributed to borrower credit risk; instead, it is significantly associated with the characteristics of the products and the origination channel in the subprime market. Thus, the results suggest that when done right and responsibly, lending to LMI borrowers is a viable proposition. Responsible borrowers and CRA lending should not be blamed for the current housing crisis.

While the results are interesting for understanding the performance difference between subprime and CRA loans, CAP has some program-specific characteristics. Though national in scope, CAP is geographically concentrated in certain markets. In addition, this analysis focuses solely on home purchase lending activities and borrowers with full or alternative documentation only. In addition, the variables available to researchers and investors are not the same as the loan officer and may not include all the measures that determine participation in CAP, subprime, or prime lending market. As such, it is unclear whether or not the findings for the CAP program are applicable to a national population of CRA loans and the entire subprime market. However, CAP borrowers are matched with subprime borrowers with similar risk profiles, focusing in this way on the less risky portion of the subprime market. Investor loans and low- or no-doc subprime mortgages have been excluded from the analyses, all of which are generally associated with a higher credit risk. Further, if borrowers are indeed steered to low- and no-doc loans in the subprime market even when they could have documented their income, as has been asserted by some observers, this would suggest that the increased risk of having one's mortgage originate in the subprime market is even greater than captured in this paper. As such, this research provides more convincing evidence of the relative risk of the CRA-type loans and the impact of loan features and origination channels on loan performance.

Endnotes

1 For more complete details of CRA regulations, see http://www.ffiec.gov/cra/default.html.

2 The CRA assessment area for a retail-oriented banking institution must include "the areas in which the institution operates branches and deposit-taking automated teller

machines and any surrounding areas in which it originated or purchased a substantial portion of its loans,'' (Avery, Bostic, and Canner, 2000, p. 712).

[3] Examples of guidelines that reduced cash required to close include: lesser of $500 or 1% from borrower's own funds; maximum LTV of 98% and maximum combined LTV (including soft seconds) of 103%; no reserves required. Examples of guideline flexibility with respect to credit history include: demonstrate six-month satisfactory payment history with four sources of credit, either traditional or non-traditional; FICO scores thresholds below 620 accepted in certain programs. Examples of underwriting flexibility in assessing the ability to repay include: maximum total ratio of debt payments to income ratio of 43%, or up to 45% if new housing payment is not more than 25% higher than prior housing payment.

[4] Examples of offsetting or combined guideline flexibilities include: maximum total ratio of debt payments to income varies from 38% to 48% with borrowers with higher credit scores allowed higher ratios; higher downpayments or reserve requirements for borrowers with FICO below 620.

[5] To qualify for the CAP program, borrowers must meet one of three criteria: (1) have income under 80% of the area median income (AMI) for the metropolitan area; (2) be a minority with income below 115% of AMI; (3) or purchase a home in a high-minority (>30%) or low-income (<80% AMI) census tract and have an income below 115% AMI.

[6] The secondary market usually classifies mortgages into different levels or loan grades, such as Premier Plus, Premier, A-, B, C, and C- based on borrower's risk profile and loan features (Chomsisengphet and Penning-Cross, 2006). Prime loans (or Premier Plus, Premier) are usually classified as A. Loans rated by the secondary market as B, C, and other categories below C are usually classified as subprime and they are sometimes referred as B&C loans. If a mortgage risk categorization that falls between prime and sub-prime, but is closer to prime, it is referred to as ''A-'' or ''A minus.''

[7] The number of seasoned loans was checked and their impact on the performance of mortgages was evaluated. For the 2005–2006 cohort, the number of seasoned loans (entered the datasets six months after origination) were quite few for both LPS loans and CAP loans (less than 7%). There were some seasoned loans for the 2003–2004 cohorts but the shares were quite similar for subprime loans (40%) and CAP loans (41%).

[8] Other common matching algorithms include: nearest-neighbor matching, kernel matching, local linear matching, Mahalanobis metric matching, Mahalanobis metric matching including the propensity score, and difference in differences methods (see review in Guo, Barth, and Gibbons, 2006).

[9] This assumption is also known as the *exogeneity, unconfoundedness, ignorable treatment assignment, conditional homogeneity,* or the *selection on observables* assumption (Guo, Barth, and Gibbons, 2006).

[10] Unfortunately, there are too few loans in the matched sample for retail-originated fixed-rate mortgages (less than 20 loans for the one-to-one match for each category), which does not allow a meaningful analysis, so they were dropped from further analysis.

[11] Of course, including adjustable-rate mortgages and fixed-rate mortgages in a single performance equation may be questionable since there are huge differences on how these types of loans perform over time and react to contemporaneous economic conditions (Pennington-Cross and Ho, 2010). However, one of the research questions of this study

is to identify whether an adjustable-rate term has increased default risk for borrowers with similar characteristics. A model focusing on the fixed rate market only was run and the results are quite consistent with the model employed in this paper (the coefficients of the subprime variables are even greater).

[12] The HHI is constructed as the sum of squared market shares of firms in a ZIP Code. Based on HMDA data, the market share of firms were identified in a census tract and then matched to corresponding ZIP Codes. When a census tract overlaps multiple ZIP Codes, it was assumed that the share of loans for the particular firm is the same as the share of other house units in the tract. As such, the index ranges from 10,000 in the case of 100% market concentration to near zero in the case of many firms with equally small market shares.

[13] The value of the put option is proxied by the ratio of negative equity (unpaid mortgage balance minus estimated house price based on the Federal Housing Finance Agency (FHFA) house price index) to the estimated house price. The MSA FHFA HPI based on the house price index was used primarily. When the property is located in an area outside MSAs, the state level HPI is used.

[14] About two-thirds (63%) of subprime loans had a LTV of 75% to 95% in this sample. When it was assumed that all these subprime loans took out second or higher liens, the estimated cumulative default rates of subprime loans was still significantly higher than that of CAP loans but the magnitude becomes smaller: the relative default risk of subprime loans becomes 2.6 times for 2004 originations to 2.8 times for 2006 originations, relative to that of comparable CAP loans. Of course, this treatment underestimates the default risk of subprime loans because not all subprime loans within that range had higher liens, while an unknown portion of CAP loans had second liens but were not considered.

[15] There may be an interaction effect between risky loan characteristics and risky borrowers. In fact, risky loan characteristics are found to have an even bigger negative impact for a ‘‘low-risk’’ (high credit score) borrower. One possible explanation is that that risky loan terms play a more important role for ‘‘low-risk’’ borrowers (the increase in their default rate is relatively higher when they receive products with risky terms) than borrowers with lower credit scores. Of course, further studies are needed to draw more concrete conclusions.

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