

Determinants of the Incidence of Loan Modifications

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1. Overview

Loan modifications give borrowers in default¹ the opportunity to reduce their interest rate, extend the term of their loan, reduce their principal balance, or add missed payments to the principal (Mason, 2007; Adelino, Gerardi, and Willen, 2009). If a loan modification helps a borrower to stay current on his or her loan, the modification may allow the borrower to avoid both the financial costs of foreclosure and the disruption and social and psychological costs of moving, and may save the borrower's credit record (Kingsley, Smith, and Price, 2009; Schloemer, Li, Ernst, and Keest, 2006). Successful modifications help the neighborhood as well, by avoiding vacancies and high rates of turnover (and the crime and other negative impacts that they may cause), avoiding decreases in neighboring property values associated with foreclosures, and promoting stability (and the social cohesion it produces) (Immergluck and Smith, 2006; Schuetz, Been, and Ellen, 2008; Harding, Rosenblath, and Yao, 2009). Lenders and investors in securitized mortgages may benefit from modifications by avoiding the costs associated with foreclosure, such as reduced property values, loss of income and deterioration in quality as the property sits vacant, and legal and administrative fees (Pennington-Cross, 2006).

Policymakers have put considerable emphasis on the desirability of modifications to help borrowers avoid losing their homes through foreclosures. A chronology of the modification programs lenders and the federal government have adopted over the past few years is attached as Appendix A. Most recently, modifications play a central role in the federal Making Home Affordable Plan the Obama administration announced in February 2009 (U.S. Department of Treasury, 2009a). The plan includes financial incentives for servicers to complete modifications of delinquent loans, principal reduction rewards for borrowers who stay current, incentive

¹ Some modifications are arranged before default, but such loans are excluded from the analysis in this paper for reasons we discuss in the Data section.

payments to servicers and borrowers for modifying at-risk loans before they become delinquent, and an insurance fund to encourage lenders to modify loans even if home prices fall in the future. Through the Home Affordable Modification Program (HAMP), the U.S. Department of the Treasury has worked to standardize loan modification practices throughout the mortgage industry by partnering with banks to develop uniform guidelines for loan modifications (U.S. Department of Treasury, 2009b).

For policymakers as well as lenders and investors, two issues are critical. First, those decisionmakers need to understand the determinants of *successful* modifications – those that allow the homeowner to stay current over the long-term. The performance of modified loans to date has been disappointing. Most recently, Fitch Research estimated in February 2011 that although redefault rates on modifications are improving, “60% -70% of modifications on subprime and Alt-A products will redefault within 12 months” and redefault rates on prime loans “are projected at 50-60% within 12 months of modification” (Fitch Ratings, 2011). Agarwal and his colleagues find that 34% of loans receiving modifications in 2008 and the first two quarters of 2009 were 60+ days past due within just six months of modification (Agarwal, et al., 2010). Moody’s Investor Services found that of the loans modified in the first half of 2010, 25% were in default again within six months, down from 31% for those loans modified in 2009 (Bay, 2011).

Second, policymakers, lenders, investors and servicers need to better understand how to achieve the efficient level of modifications. The efficient level of modifications depends, of course, upon accurate assessments of the long-term success rates of modifications versus accurate assessments of the full extent of losses incurred when the loans are not modified. To our knowledge, no one has attempted to quantify what the efficient level of modifications would be, but the perception of many policy-makers is that the number of modifications agreed to has

been woefully inadequate.

Too little is known even about the most basic questions about the determinants of modifications that would help us understand those two issues: Which borrowers receive modifications? Are certain loan provisions associated with the likelihood that the loan will be modified? Do the characteristics or identity of lenders or servicers affect the propensity of borrowers to receive modifications? Do characteristics of the property, or the neighborhood in which it is located, affect the propensity of loans to be modified? What role, for example, does residential segregation – the concentration of minorities in a neighborhood– play in the propensity of borrowers to get modifications?

In this paper, we shed new light on these issues about the borrowers and loans receiving modifications by using a unique combination of data on borrowers in New York City. In a subsequent paper, we will then use that information to examine the features of the borrower, loan, lender, neighborhood and property that predict which modifications will succeed in keeping borrowers in their homes over the long term.

This paper will build upon the existing literature by combining a dataset the Furman Center for Real Estate and Urban Policy has built on borrower, neighborhood, and property characteristics for loans originated in New York City with the OCC's Mortgage Metrics dataset to examine the determinants of loan modifications. Identifying the features of borrowers, loans, lenders, servicers, properties and neighborhoods that are associated with loan modifications will allow lenders and policy-makers to target modification programs for distressed mortgage borrowers more effectively. The unusually rich combination of data also will allow us to assess whether borrowers and servicers are acting rationally in deciding whether to modify a loan, analyze whether models that do not incorporate the detailed borrower and neighborhood data we

provide may be misleading, and assess whether there are any characteristics of loans, borrowers or neighborhoods that make modifications especially challenging given the current economic and regulatory framework.

2. Background and Literature Review

When a borrower falls behind on her home mortgage payments, a variety of resolutions or outcomes are possible. First, if the borrower is delinquent or in default, but has not yet received a notice of foreclosure (*lis pendens*), the borrower and/or lender (or servicer acting on behalf of the lender or on behalf of the investors in securitized mortgages) have several options: (i) the borrower can cure the delinquency or default by making some or all of the missed payments; (ii) the borrower and the lender can agree to modify the loan; (iii) the borrower can refinance the mortgage; (iv) the borrower can sell the property either for enough to pay off the balance remaining on the mortgage, or through a “short sale,” whereby the lender agrees to accept a purchase price of less than the balance remaining in satisfaction of the mortgage; (v) the borrower can pre-pay the mortgage by drawing on other resources; or (vi) the borrower can continue to be delinquent or in default, but the lender can choose to forbear on the delinquency or default without beginning foreclosure, or set a repayment plan in which the borrower typically pays back any late payments in small installments on top of the existing mortgage installments. Second, if the lender/servicer has begun the foreclosure process, either by filing a *lis pendens* in a judicial foreclosure state or by sending a Notice of Default to the borrower in a non-judicial foreclosure state², the borrower can pursue any of those six paths, and in addition may: (vii) give the lender/servicer a deed in lieu of foreclosure; (viii) lose the property to the lender/servicer in

² In this paper, we focus only on loans in New York, a judicial foreclosure state where a *lis pendens* can be filed if a borrower is at least 90 days delinquent.

the foreclosure auction (“REO” property); or (ix) lose the property to a third party in a foreclosure auction. Either before or after the foreclosure process has officially begun, therefore, the lender/servicer and borrower may reach an agreement to modify the terms of the loan.

According to U.S. Department of Treasury (2008, 2010b), the number of loan modifications issued has been consistently increasing since October 2007 (the inception of the OCC data collection), with over 1.5 million permanent modifications completed nationally as of June 2010. The literature about the determinants of modification, however, is thin. Cordell, Dynan, Lehnert, Liang, and Mauskopf (2008) suggest as a theoretical matter that securitization may negatively affect the probability of modification, because modifications of non-GSE securitized mortgages are hampered by servicers’ lack of investment in staff and technology needed for modifications, by the lack of guidance servicers have received from private Mortgage Backed Securities pools about how to determine which mortgages should be modified, and by the high delinquency recidivism rate of such mortgages. In addition, the authors assert that subprime loans are especially challenging to modify because it is more difficult to make such mortgages affordable than it is to do so with prime mortgages, and because subprime mortgages are more often paired with junior liens.

Empirically, Piskorski, Seru, and Vig (2009) find that delinquent loans held in the lender’s portfolio were less likely to foreclose than securitized loans, and posit that servicers of securitized mortgages face significant costs associated with renegotiating loans that discourage them from making modifications. The authors use loan level data from Lender Processing Services (LPS) (formerly called McDash Analytics) on first lien loans, and restrict the analysis to fully documented loans in order to address potential selection bias between securitized loans and those held by a bank.

In contrast, Foote, Gerardi, Goette, and Willen (2009) find that securitized and non-securitized loans are modified at about the same rate. The authors find evidence that most modifications result in increased monthly payments, and that modifications that result in increased monthly payments are much more likely to end in foreclosure than those that result in lower payments. The authors did not have access to direct information about modifications in data they were using -- the LPS data, and therefore use an indirect method to identify modifications.

Adelino, Gerardi, and Willen (2009) suggest that mortgages in default that are subprime and have lower credit scores and higher loan-to-value ratios (LTVs) are more likely to receive modifications than other mortgage loans in default. The authors use a sample of loans from LPS and a series of logit models to estimate the marginal effects of different loan characteristics on the probability of modification. However, like Foote, Gerardi, Goette, and Willen (2009), they were unable to access specific information about modifications, and had to use an indirect identification process.

Agarwal (2010) and his colleagues use the OCC's mortgage metrics database (the same database that we use in this paper) to evaluate the modification or other outcome of mortgages that became seriously delinquent between January 2008 and June 2009. Using regression analysis in which the dependent variable is the probability of one of the possible outcomes of the delinquency within six months of the delinquency, they find that the likelihood of modification of securitized loans is up to 70% lower than the likelihood for portfolio loans. They also find considerable variation in the practices of different servicers that cannot be explained by differences in the loans they service; indeed the identity of the servicer explains as much variation in modification terms as the characteristics of the borrowers. They find that greater

reductions in mortgage payments or interest rates are associated with lower default rates in the six months following modification. However, the models they used to study the outcomes of delinquent loans do not account for the competing risk nature of these outcomes, thus raising concerns about model mis-specification biases. Additionally, their models for the performance of modified loans include only one modification feature (e.g., interest rate reduction) at a time, thus raising concerns about omitted variable bias in the coefficient of the included feature (which may be correlated with the omitted features).

There is more research on outcomes after default other than modifications. Ambrose and Capone (1996), for example, focus on foreclosure and find that, after default, the foreclosure rate of minority borrowers is very similar to that of white borrowers, and lenders tend to offer minorities more time to work out their situation before initiating foreclosure. Their analysis is limited, however, to descriptive statistics, and does not control for the influence of other potentially relevant variables. In addition, their analysis may not be representative of the current conditions because it is based on data from the beginning of the 1990s, a period long before the onset of massive securitization, when lending standards may have been different.

Capozza and Thomson (2006) analyzed a rich set of data on a sample of 6,000 subprime mortgages issued by a single lender that were at least 90 days delinquent on September 30, 2001 to identify determinants of the mortgages' status eight months later. They found that loans with high interest rate premia were less likely to be foreclosed, perhaps because lenders have a greater incentive to forbear when the loan carries an interest rate favorable to the lender. They also found that lenders are more likely to foreclose on loans with fixed interest rates, standard documentation and high loan-to-value ratios, and less likely to foreclose during times of declining interest rates or high levels of economic growth (perhaps because defaults when the

economy is strong are more likely to have been triggered by the borrower's bad luck, such as a health crisis or divorce). Lenders also are more likely to forbear when the borrower has made more payments, and when the payment to income ratio is high. The generalizability of these findings may be limited, however, because the loans were issued by a single lender, and were originated prior to 2001, before the boom in subprime home purchase mortgage lending and the recent dramatic rise and fall of housing prices.

Pennington-Cross (2006) used a sample of 5,000 fixed rate subprime loans to estimate a competing risk multinomial logit model of the outcomes of delinquency (defined as termination, cure, partial cure, or REO), and found that almost all loans that began the foreclosure process were ultimately terminated. He found that several borrower, loan, and neighborhood factors, including the equity in the home, local unemployment rates and market interest rates, influence the probability of these outcomes. More recently, Pennington-Cross and Ho (2010) used a sample of 173,000 fixed and adjustable rate mortgages originated between 1998 and 2005 to estimate a competing risk model of loan terminations through default or prepayment. They found evidence that borrowers who expect to sell their property or refinance their loan self select into using ARMs. They also found that the magnitude of the payment shock when the ARM interest rate resets is highly correlated with the propensity to default, with larger payment shocks increasing the default probability.

Voicu, Jacob, Rengert, and Fang (2011) merged data from Loan Performance Corp. with that from the Home Mortgage Disclosure Act dataset to study the determinants of a variety of default resolutions. They found that product features affect the probability of various outcomes: ARMs, interest-only, and loans with low- or no-documentation are more likely to enter foreclosure proceedings conditional on default, and more likely (conditional on entering

foreclosure proceedings) to end up as REO. They also found that demographics affect default outcomes. Owner-occupancy is associated with lower likelihood of foreclosure initiation and REO, and greater likelihood of curing default. Non-Hispanic Asians are more likely than non-Hispanic whites to terminate their loans as REO if they enter foreclosure, and are less likely to cure at all stages of the process. Non-Hispanic blacks are less likely to enter foreclosure if they default than are non-Hispanic whites. Additionally, default outcomes are impacted by local legal, economic and housing market conditions, and the equity in the home.

In a 2009 study, Abt Associates used data on loans in five mid-Atlantic states and Washington, D.C. for which Wells Fargo serves as the trustee. They found evidence to suggest that there is wide variation across servicers in the incidence of loan modifications and other outcomes. However, their sample was limited both geographically and by the servicers involved.

The existing literature, accordingly, does not focus much on the determinants of modifications, for which high quality data has only recently become available. The research on the determinants of other outcomes upon default can help to inform our understanding of what might determine the propensity of distressed borrowers to receive modifications. But modifications are likely to be influenced by somewhat different factors, both because modifications require more interaction between the borrower and lender than many of the other outcomes studied, and because the political and economic climate of the foreclosure crisis may be leading to modifications that would not take place in less difficult times. But even if the determinants of, e.g., cure, are similar to the determinants of modification, the existing literature on those other outcomes is limited by its focus on either single lenders or a constrained range of mortgage products.

3. Theoretical Model and Empirical Strategy

This paper provides an empirical analysis of the factors that determine the outcomes of seriously delinquent loans (loans at least 60 days delinquent). Theoretically, the outcomes are the process of a negotiation between the borrower and the lender (or servicer acting on behalf of either the lender or the investor if the mortgage has been securitized). For expositional ease, we will refer to the borrower's counterparty in the negotiations as the servicer. The borrower is acting to minimize the loss of any equity she has invested, minimize the costs of the delinquency, and minimize the cost of carrying the mortgage in the future. The servicer is acting to maximize the return the mortgage provides to the investors or lender. The servicer may have interests that differ from the lender's or investors', of course, so a more accurate and complete model would account for the different interests of the borrower, lender/investor and servicer. We have almost no information about the servicers involved in the mortgages we study, however, because the identities of the servicers were withheld in the data. Further, the interests of the servicers are tied to the structure of their compensation for foreclosing on the loan versus the compensation received for other outcomes. Those incentives may explain why a servicer would allow a delinquent loan to remain delinquent without taking any action to foreclose or otherwise address the delinquency, or may explain why a servicer would foreclose on a loan rather than reach a modification or other workout. Unless those incentives depend upon characteristics of the borrower, loan, property or neighborhood, however, it is reasonable to assume that although the servicer may not be a faithful agent in deciding where to draw the line between the number of loans foreclosed versus modified, for example, its decision about *which* loans to foreclose versus modify should not be distorted by its own interests and should be subject to monitoring by the lender/investor.

We further assume that a servicer acting as a faithful agent of the lender or investor in deciding which outcomes are appropriate for a loan with particular characteristics is basing that decision on the net present value test set forth in the Hope for Homeowners Act of 2008:

(a) In General—Except as may be established in any investment contract between a servicer of pooled residential mortgages and an investor, a servicer of pooled residential mortgages—

. . . (2) shall be deemed to act in the best interests of all such investors and parties if the servicer agrees to or implements a modification or workout plan, . . . provided that any mortgage so modified meets the following criteria: . . .

(C) The anticipated recovery on the principal outstanding obligation of the mortgage under the modification or workout plan exceeds, on a net present value basis, the anticipated recovery on the principal outstanding obligation of the mortgage through foreclosure. (emphasis added).

In addition, we assume that the servicer is cognizant of the incentive effects that its actions on one mortgage might have on borrowers who hold similar mortgages and are not in default. In other words, the servicer will seek to avoid granting modifications where doing so might encourage similarly situated borrowers to strategically default.

Our empirical strategy to explore the determinants of the outcomes of delinquent loans employs multinomial logit models in a hazard framework to explain how loan, borrower, and neighborhood characteristics affect which of the following five groups of outcomes, as depicted in Figure 1, results from a seriously delinquent loan: (1) the borrower cures the delinquency (all past due amounts are paid by the borrower, or the loan balance is paid off via a regular sale or refinance); (2) the servicer modifies the loan; (3) the borrower and servicer agree on some other non-liquidation workout (i.e., forbearance, repayment plan, FHA partial claim,³ loan

³ An FHA partial claim might be used if the Federal Housing Administration (FHA) insured the loan. A one-time payment is made by the FHA to the lender to cover all or a portion of the default; the borrower is required to sign an interest free note for the amount of the advance claim payment payable to the FHA; the promissory note is not due and payable until the homeowner either pays off the first mortgage or no longer owns the property

reaged/deferred/extended,⁴ other⁵); (4) the borrower suffers a liquidation (short sale, deed in lieu, foreclosure auction sale or REO); or (5) the loan becomes more months delinquent.⁶ Although our data includes detailed information on the type of modification (e.g., interest rate reduced; term extended; principal write-down, etc.), we do not distinguish among the different types in this paper primarily due to the large number of types and the relatively small number of loans in a given type. These features of the modification data together with the large number of categorical covariates used in the empirical model and the large sample size make the estimation practically infeasible if detailed modification types were included.⁷

The data is organized in event history format, with each observation representing one month in which a seriously delinquent loan remains in default, to allow for time-varying covariates. A loan drops out of the sample after one of the outcomes 1 to 4 occurs. With the data structured in event history format, the multinomial logit has the same likelihood function as a discrete time proportional hazards model (Allison, 1995). In addition, the multinomial logit model directly accounts for the competing risks of the various outcomes (i.e., in each month, the loan can be in only one state - delinquent, cured, modified, etc.) by imposing the restriction that

⁴ "Reaged/Deferred/Extended" includes, according to the data provider, workouts where there has been an agreement between servicer and borrower to defer principal and interest but with no other terms to enhance affordability.

⁵ "Other" typically includes, according to the data provider, alternative loss mitigation strategies designed to provide temporary help, such as partial claims and Fannie Mae's HomeSaver Advance. The former is similar to the FHA partial claim except that the insurer is a private entity. The latter is designed for the borrower who is otherwise capable of meeting his obligations and will be able to resume timely payments once the arrearage is brought current; under the program, Fannie Mae authorizes its servicers to offer an unsecured personal loan that will enable a qualified borrower to cure the payment default on a Fannie Mae owned or securitized loan; this personal loan has fewer up-front costs and can be put in place more quickly than many other options.

⁶ The "Cure" outcome also includes loans that become 30-day delinquent, as long as they stay 30 DPD until the end of the study period or become current by then, with none of the other outcomes occurring; however, if a loan becomes 30DPD or current and then reverts to serious delinquency, we consider the loan seriously delinquent and follow it until the end of the study period or until another outcome occurs – whichever comes first.

⁷ More specifically, the small number of observations for a given modification type together with the large number of categorical covariates would likely result in many empty cells which would make it impossible to reliably estimate many coefficients in the multinomial logit models we use. In addition, the large number of modification types together with the large sample size would require extraordinary computer resources to estimate our multinomial logit models.

the sum of the probabilities of the possible outcomes is equal to one. In the multinomial logit framework, the probability of each of the 5 outcomes described above is given by:

$$\text{PROB}(O_{it} = j) = \frac{e^{\beta_j X_{it}}}{1 + \sum_{j=1}^4 e^{\beta_j X_{it}}}, \text{ for } j=1, 2, 3, 4$$

$$\text{PROB}(O_{it} = j) = \frac{1}{1 + \sum_{j=1}^4 e^{\beta_j X_{it}}}, \text{ for } j=5,$$

where $\text{PROB}(O_{it} = j)$ is the probability that the i th loan will have outcome j in month t , outcome (5), the loan becoming additional months delinquent, is the reference outcome, X_{it} are the explanatory variables, and β_j are the coefficients to be estimated. To put this notation in the hazard framework, $\text{Prob}(O_{it}=j)$ is the hazard rate for outcome j . For example, if outcome j is (1), cure, then $\text{Prob}(O_{it}=j)$ is the conditional probability that the loan will leave delinquency through cure in month t conditional on the loan “surviving” in delinquency until then.

We include time since default among the covariates to allow the hazard rate to be time-dependent. The coefficient estimates are used to calculate the marginal effects of the explanatory variables on the probability of each outcome. To control for city-, state-, or nationwide macroeconomic factors, we include quarterly fixed effects. To control for systematic changes in mortgage lending over time, we include origination year fixed effects.

To control for unobserved heterogeneity and possible dependence among observations for the same loan, we use a cluster-robust variance estimator that allows for clustering by loan. The independence of irrelevant alternatives (IIA) assumption⁸ - a main drawback of the multinomial logit model - is not a concern in our case, because the Small-Hsiao test cannot reject the IIA assumption for our data.

⁸ This assumption implies that the odds ratio of a pair of outcomes is independent of any of the alternative outcomes.

4. Data Description

To investigate the determinants of modifications, we analyze outcomes between January 2008 and January 2010 for all first lien mortgages originated in New York City from 2004 to 2008 and still active as of January 1, 2008 in OCC Mortgage Metrics. OCC Mortgage Metrics is a special extract of the LPS Applied Analytics database that includes detailed information about loan modifications not usually reported in LPS.⁹ As with the standard LPS database, Mortgage Metrics includes loans serviced by 12 large mortgage servicers covering approximately two-thirds of all mortgages outstanding in the United States and includes all types of mortgages serviced, including subprime mortgages.¹⁰ Nationally, the loans in the OCC Mortgage Metrics dataset represent a large share of the overall mortgage industry, but they do not represent a statistically random sample of all mortgage loans. For example, only the largest servicers are included in the OCC Mortgage Metrics, and a large majority of the included servicers are national banks. Thus, the characteristics of these loans may differ from the overall population of mortgages in the United States. For example, subprime mortgages are underrepresented and conforming loans sold to the GSEs are overrepresented in the OCC Mortgage Metrics data (U.S. Department of Treasury, 2008).

An observation in the data set is a loan in a given month. Although we look at

⁹ In addition, the quality of OCC Mortgage Metrics data is likely higher than that of the LPS data because the OCC and OTS went to great lengths to standardize the reporting of the variables across lenders and to correct data entry errors. On the other hand, the LPS data follows loan performance since origination, while the OCC Mortgage Metrics follows loan performance only since the beginning of 2008.

¹⁰ The number of servicers in the OCC Mortgage Metrics has varied over time since the onset of the data collection in 2007, primarily due to mergers and acquisitions among the initial servicers that provided the data. As of the end of 2009, the servicers in the OCC Mortgage Metrics included nine national banks and three thrifts with the largest mortgage-servicing portfolios among national banks and thrifts (U.S. Department of Treasury, 2010). The OCC Mortgage Metric extract for New York City includes 11 servicers.

originations between 2004 and 2008, monthly performance history for those loans is only available from January 2008 through January 2010. If a loan was originated in 2004 and went through foreclosure proceedings in 2007, therefore, we will never see that loan. Although OCC Mortgage Metrics provides detailed information on borrower characteristics, loan terms, payment history and modifications, it contains no information on borrower race or gender and provides little information about property or neighborhood characteristics. We therefore supplement the loan level data with information from multiple sources.

To match loan level information from the OCC Mortgage Metrics database to other sources, we relied on mortgage deeds contained within the New York City Department of Finance's Automated City Register Information System (ACRIS). Using a hierarchical matching algorithm, we were able to match 65 percent of the loans in the OCC Mortgage Metrics database back to the deeds records, which thus gave us the exact location of the mortgaged property.¹¹ This 65 percent sample is not significantly different from the full universe in terms of the loan and borrower characteristics that we use in the analyses below.

¹¹ Our procedure for matching OCC Mortgage Metrics to ACRIS is similar to the method used by Chan et al. (2010) to match LoanPerformance to ACRIS. Our data from ACRIS do not include Staten Island and thus we had to drop this borough from our analysis. We merged OCC Mortgage Metrics loans to ACRIS mortgage deeds using three common fields: origination or deed date, loan amount and zip code, using six stages of hierarchical matching. At the end of each stage, loans and deeds that uniquely matched each other were set aside and considered matched, while all other loans and deeds enter the next stage. Stage 1 matched loans and deeds on the raw values of date, loan amount and zip code. Stage 2 matched the remaining loans and deeds on the raw values of date and zip code, and the loan amount rounded to \$1,000. Stage 3 matched on the raw values of date and zip code, and the loan amount rounded to \$10,000. Stage 4 matched on the raw values of zip code and loan amount, and allowed dates to differ by up to 60 days. Stage 5 matched on the raw value of zip code, loan amount rounded to \$1,000, and allowed dates to differ by up to 60 days. Stage 6 matched on the raw value of zip code, loan amount rounded to \$10,000, and allowed dates to differ by up to 60 days. We believe it is valid to introduce a 60-day window because in ACRIS, there may be administrative lags in the recording of the deeds data. The chance of false positive matching is low because we are matching loans to the full universe of deed records, and only considering unique matches. The relatively low match rate of 65 percent is due to the fact that we were unable to match loans made on coop units in the OCC Mortgage Metrics data to ACRIS deeds because coop mortgages are recorded differently in ACRIS and do not list a loan amount. During our study period, 28.2% of residential property sales in the four boroughs studied were coops. Further, our match rate was lowest (44%) in Manhattan where 48% of sales during the study period were of coop units. This evidence suggests that had we been able to exclude coop loans from our original OCC Mortgage Metrics dataset prior to matching to ACRIS, our final match rate would have been much higher (around 90%).

After we had a unique parcel identifier matched to each loan record, we were able to match on many other sources. First, we attach some additional borrower characteristics, including race and ethnicity, from Home Mortgage Disclosure Act (HMDA) data.¹² Second, we incorporate information on whether the borrower took on additional mortgage debt following loan origination, obtained from the New York City Department of Finance (DOF)'s Automated City Register Information System (ACRIS). Third, we merge information from the DOF's Real Property Assessment Database (RPAD) on building characteristics. Fourth, we merge information on whether the borrower received foreclosure prevention counseling or other assistance (including legal services) from any of the non-profit organizations coordinated by the Center for New York City Neighborhoods (CNYCN)¹³. Fifth, we merge in repeat sales house price indices the Furman Center for Real Estate and Urban Policy compiles to track appreciation in 56 different community districts of New York City.¹⁴ Sixth, we link information on the demographic characteristics of census tracts using the 2000 Census. Seventh, we add the rate of mortgage foreclosure notices (*lis pendens*) at the census tract level.¹⁵ Eighth, we attach monthly crime rates at the census tract level using a database obtained from the New York City Police Department. Finally, using all loans in the LPS data (not just the seriously delinquent ones), we

¹² We merged HMDA records to ACRIS deeds based on date, loan amount and census tract, using the same six stage hierarchical matching technique as for the OCC Mortgage Metrics-ACRIS match. We then paired each of the OCC Mortgage Metrics records with HMDA records based on the unique deed identification number from ACRIS. In the end, we were able to match 73 percent of the OCC Mortgage Metrics-ACRIS matched loans (or 48 percent of all OCC Mortgage Metrics loans) to the HMDA records. While other researchers have matched loan level data (such as OCC Mortgage Metrics) directly to HMDA by using the zip code as a common geographic identifier, our matching strategy is likely more reliable as it uses a more precise common geographical identifier (census tract).

¹³ CNYCN is a non-profit organization, funded by grants from government, foundations, and financial institutions, to coordinate foreclosure counseling, education, and legal services from a variety of non-profit providers throughout New York City to homeowners and tenants at risk of losing their home to foreclosure. CNYCN directs borrowers facing trouble with their mortgages who call 311 or CNYCN directly to local foreclosure counseling or legal services. Each of its partner organizations then reports back to CNYCN on which borrowers received foreclosure prevention counseling or legal services.

¹⁴ See Armstrong et al. (2009) for a description. We transform quarterly indices into monthly series by linear interpolation.

¹⁵ The *lis pendens* are from Public Data Corporation. The rate is computed as the number of *lis pendens* per 1000 housing units recorded over the 6-month period preceding the month of loan performance.

construct each servicer's share of the loans which were originated in the zip code between 2004 and 2008 and were outstanding and serviced by one of the LPS servicers at some point in 2008 or 2009.

When available, we matched data at the observation level to show information about the specific property being studied. When observation level data was not available (e.g., educational attainment) or was not appropriate (e.g., 6 month prior neighborhood *lis pendens* rate) we used neighborhood level data instead. We define neighborhood as a census tract, the smallest geographic level available, whenever possible. However, for several data sources, census tract data was not available, so we had to use community district or zip code level data.¹⁶ The change in the unemployment rate and the rate of house price appreciation were calculated at the community district level, and the servicer's share of the outstanding loans was computed at the zip code level; all other neighborhood characteristics are census tract level. To illustrate the relative size of each jurisdiction, Figure 2 shows census tract boundaries, community district boundaries and foreclosures in the four boroughs of New York City in 2009.¹⁷

4.1 Descriptive Statistics

Table 1 presents descriptive statistics for the dataset used in the estimation, organized in four panels: A – distribution of outcomes; B – loan characteristics; C – borrower and property characteristics; and D – neighborhood characteristics. Panel A shows that only 9 percent of the seriously delinquent loans in our data received a modification, and another 8 percent received

¹⁶ Community districts are political units unique to New York City. Each of the 59 community districts has a Community Board whose members are appointed by the Borough President of that district; half of the members are nominated by the City Council members who represent the district. The Community Boards review applications for zoning changes and other land use proposals, and make non-binding recommendations about those proposals. They also recommend budget priorities.

¹⁷ For readability purposes, we do not show zip code boundaries in this map. We note however that the typical zip code size, both in terms of area and population, is larger than the typical census tract size but smaller than the typical community district size.

other workouts including a repayment plan (1.3%), a forbearance plan (0.5%), or an undefined workout (6.3%). About 15 percent of the loans were cured through the borrower's own efforts, about 5 percent experienced liquidation, and the remaining loans (almost two thirds of the total) remained in serious delinquency during the whole study period. The shares of loans going into particular outcomes may differ between New York City and other cities or the nation as a whole for two reasons: 1) house prices in New York City peaked later and have fallen less precipitously than in many other cities and 2) New York State has a longer, more protracted judicial foreclosure process than most states.

Panel B presents descriptive statistics for the characteristics of the loans in our dataset. Our dataset covers a range of loan products. Of the 29,366 seriously delinquent loans in our dataset, there is a nearly even split between prime and non-prime loans, 60% have fixed interest rates while the remainder have adjustable rate mortgages, 20% were interest only at origination and 78% are conventional mortgages. Home purchase loans make up 43% the loans in our sample, while 35% are refinances. Our sample also includes a mix of loans that have been privately securitized, bought by the GSEs and held in portfolio. This robust mix of loan products, uses and investors allows us to advance the literature because our conclusions are not limited to only one loan type or group of loans. The servicers in our sample serviced an average of 18% of the outstanding loans in each zip code of the loan origination.

The relative interest rate at origination for FRMs is calculated as the interest rate minus the Freddie Mac average interest rate for prime 30-year fixed rate mortgages during the month of origination. For ARMs, it is the interest rate minus the six-month London Interbank Offered Rate (LIBOR) at origination. In our sample, over 40% of the fixed rate loans have relative

interest rates between 0 and 1 percent and nearly 50% of the adjustable rate loans have relative interest rates between 2 and 4 percent at origination.

Because certain characteristics of the loans change over time, we construct loan-months for every month during our study period in which a loan was active, for a total of 258,326 loan-months. The last two descriptives in Panel B are measured across all loan-months in our sample, and show that in 33% of the loan months, the borrower had a junior lien on the property, originated either at the same time as the first lien or after the first lien but prior to the loan-month. The average LTV for all of the loan months in our sample was 101.8%.¹⁸ This reflected an average 24 percentage point increase in LTV since origination.

As Panel C shows, nearly 90% of the borrowers in our sample report that they are owner-occupiers. The property types in the sample are relatively evenly mixed between single family homes or condominiums and 2-4 family homes. That mix is fairly reflective of the owner-occupied housing stock in New York City. According to the 2009 American Community Survey, just 42 percent of homeowners in New York City live in single-family homes, compared to 88 percent nationwide, 86 percent in Los Angeles and 57 percent in Chicago. The remainder of the homeowners in New York City live in one unit of a two to four unit building or own a condominium or cooperative apartment in a larger building. We constructed borrower months for those borrower level variables that change over time. The current FICO score (reported quarterly for each borrower) has a mean of 556 across all borrower-months, and 75% of borrower-months have FICO scores of 620 or less. On average, FICO scores of delinquent borrowers in our sample declined by 111 points from origination to the month being studied. Foreclosure counseling is also measured in loan-months to ensure that we are capturing

¹⁸ LTV is based on the first lien only. We do not have data on outstanding balances, delinquencies or other outcomes for junior liens.

counseling that occurred prior to the outcome; 2.2 percent of all borrowers received counseling at some point prior to the outcome (or the end of the study period if no resolution occurred).

The characteristics of the neighborhoods in which the properties in our sample are located (shown in Panel D) largely mirror the neighborhood characteristics of the four boroughs of New York City included in our analysis, except that properties in our sample are: (1) more likely to be located in neighborhoods with high concentrations of non-Hispanic blacks; (2) less likely to be located in neighborhoods with high concentrations of Hispanics; and (3) more likely to be in neighborhoods with median incomes between \$40,000 and \$60,000 and less likely to be in neighborhoods with median incomes less than \$20,000 or more than \$60,000.¹⁹

Panel D also reveals some interesting neighborhood shifts from loan origination to loan month studied. On average, the community district unemployment rate increased by two percentage points. Further, in the neighborhoods where the loans in our sample are located, house prices decreased by an average of 19.3 percent between origination and the loan month being studied.

Our model also includes servicer fixed effects. Panel E shows the range of FICO scores and LTV ratios at the time of loan origination for the delinquent loans in our sample across the 11 servicers covered in the OCC Mortgage Metrics Data for New York City.²⁰ Average FICO scores range from 656 to 698. LTVs range from .451 to .800.

For this analysis, we chose to focus on seriously delinquent loans because borrowers who receive modifications without ever being seriously delinquent may differ from seriously delinquent borrowers who receive modifications in several ways. First, those borrowers who

¹⁹ Not surprisingly, given that owner-occupier borrowers are by definition homeowners, properties in our sample are located in neighborhoods with higher homeownership rates than the average neighborhood in the four boroughs we studied.

²⁰ Note, however, that our models only have 9 servicer dummy variables (one of which is excluded as the reference servicer) because two servicers had too few loans to be accounted for with separate indicators.

receive modifications without ever being seriously delinquent may be savvier and better able to negotiate the modification process than the seriously delinquent borrowers who receive modifications. Second, borrowers who have never been seriously delinquent may receive modifications because loan servicers target certain borrowers for modifications (e.g., borrowers for whom the default is deemed imminent due to a forthcoming lay-off or other event that will affect the ability to pay in the foreseeable future). Third, borrowers who receive modifications without being seriously delinquent may have loans that are systematically different in ways that made those loans easier or more attractive for servicers to modify. Although we are unable to empirically explore the first and second hypotheses, Table 2 presents descriptive evidence that supports the third hypothesis

5. Results

Table 3 presents odds ratio estimates for the multinomial logistic regression described above. Below, we review in detail the results on the determinants of loans modifications (which are the focus of this paper) and provide an overview of the results for the other default outcomes included in the analysis.

5.1 Determinants of Modifications

Loan characteristics. The first set of rows in Table 3 show the impact the loan type has on outcomes. Loans that the servicer defines as non-prime at origination were more likely to be modified than prime loans. However, adjustable rate and interest only mortgages were less likely to be modified than fixed rate mortgages, perhaps because these risky loans would require the most drastic modifications. Fully documented loans are more likely to be modified than no-

doc loans, perhaps because lenders require full documentation before issuing a modification. The purpose of the loan (whether for home purchase or refinance) does not affect the likelihood of receiving a modification. Contrary to Foote, Gerardi, Goette, and Willen (2009), but consistent with Piskorski, Seru, and Vig (2009) we found that loans held in portfolio were significantly more likely to be modified than securitized loans held by private investors. Securitized loans guaranteed by the GSEs were less likely than all other loans to be modified, perhaps because the incentives the servicers of GSE loans had, or the processes they used, may have been systematically different.

We next focus on the pricing of loans at origination. For FRMs, interest rate spreads above the market average rate are associated with a lower likelihood of modification. Consistent with other research (Chan, et al 2010), if we interpret the loan pricing terms to reflect *ex ante* risk pricing by lenders, these coefficients could be picking up some borrower risk that is not reflected in the specific risk controls we include in our model. If so, the servicer might be wary of extending modifications to borrowers that the originating lender had evaluated as being more risky.

For ARMs, loans with higher interest rates at origination are more likely to be modified, with the highest likelihood when the rate was up to two points higher than the index. It may be that teaser rates for ARMs make the interest rate at origination for ARMs a less accurate signal of borrower risk than the rate at origination for FRMs. Or higher rates at origination for ARMs may be associated with lower probabilities of default after reset (because the adjustment may be lower than the adjustments of low teaser rates), and thereby make the borrower a more attractive candidate for modification. We find that the likelihood that a loan is modified decreases as the time since the initial adjustment increases. Again, this finding may reflect a reasonable concern

of either the borrower or the servicer about the likelihood that the modification will be successful in the long run. Defaults further out from the adjustment may be more likely to be related to job loss or other crises that would make any modification difficult to sustain, while delinquencies soon after an adjustment may signal that the family is just having trouble with the increase, but is otherwise still solvent.

A property's current LTV has a significant, large, and monotonically increasing effect on the likelihood of modification. As LTV increases, the servicer may realize that the lender or investor would lose more if the servicer forecloses on a property rather than modifying, and thus be more inclined to keep the borrower in the property by modifying. Consistent with the findings of Cordell, et al (2008), if the property has a second lien attached to it, the loan is significantly less likely to be modified. Without the cooperation of the second lien holder, it makes no sense for a servicer to modify a loan. Older loans are more likely to be modified, perhaps indicating a servicer's willingness to work with a borrower who has a track record of being reliable. A longer time in default is associated with a decreased propensity for modifications, perhaps because borrowers who want modifications seek them out very soon after defaulting on their loan or because servicers target modifications to borrowers who have only recently become delinquent.

Finally, we find that the propensity to modify loans does not vary substantially across servicers. Only 3 out of the 8 servicer dummy variables included in our model have statistically significant odds ratios with respect to the modification outcome.²¹ Additionally, we find little variation in the probability of modification with respect to the servicer's presence in the neighborhood, as measured by the share of loans the servicer serviced in the neighborhood in recent years. These findings may reflect the increasing government efforts to standardize the

²¹ In addition, one of the 3 statistically significant odds ratios is only significant at the 10 percent level.

modification process across servicers, or may reflect the fact that securitization of the loans may have made it impossible for any particular servicer to benefit the lenders/investors it is working for by coordinated action on particular loans.

Property and Borrower characteristics. Consistent with prior literature and the current regulatory framework, loans on owner-occupied properties are more likely to be modified than investor-owned properties. Further, loans on 2-4 unit or 5+ unit rental apartment buildings are less likely to be modified than loans on single-family buildings or condo units. A greater decline in a borrower's FICO score from loan origination to the first delinquency (so, before the delinquency itself had an impact on the score) is correlated with a lesser likelihood of the loan being modified. Servicers may see borrowers whose FICO scores had declined greatly as bad candidates for modifications because they appear to be undergoing some other financial hardship. However, controlling for this decline in the model, borrowers with higher current FICO scores were less likely to receive modifications, perhaps indicating that servicers were unwilling to modify loans for borrowers that may be strategically defaulting. The race or ethnicity of the borrower had no significant impact on the likelihood that a loan would be modified, except in one respect: non-Hispanic Asians were less likely to have their loans modified than non-Hispanic whites. Consistent with Fang, Jacob and Voicu (2009), one possible explanation for this racial disparity is that language barriers may make the complex negotiations needed to secure a modification more challenging for Asian borrowers. We did not find a significant relationship between a borrower's receipt of foreclosure counseling and the likelihood that their loan would be modified. However, just 2.2 percent of the borrowers in our sample had received counseling.

Neighborhood characteristics. Table 3 also explores how the housing market conditions in a neighborhood affect the likelihood that a loan on a property within the neighborhood will be modified. Loans on properties in neighborhoods with high foreclosure rates in the six months prior to the loan month being studied are less likely to be modified, and the likelihood decreases as the foreclosure rate increases. One of the strongest predictors of modification in our model is how the rate of house price depreciation compares to rates in other neighborhoods.²² Specifically, in neighborhoods where properties have lost value since the loan was originated, the probability of getting a modification is higher in those neighborhoods with lower rates of depreciation, relative to other comparable neighborhoods. By comparison, the probability of modification varies little with the appreciation rate in neighborhoods in which housing values have increased since the loan was originated. Loans on properties in neighborhoods with just above 0 appreciation rate and those in neighborhoods with just below 0 appreciation rate have similar probability of receiving a modification (i.e., there is no discrete “jump” in the probability of modification around the 0 appreciation rate). These findings suggest that servicers acting to minimize lender/investors’ losses may be wary of offering modifications in the hardest hit neighborhoods because those may have little chance of recovering in the short term. The lower the depreciation rate the stronger the servicer’s incentives to modify in order to minimize lender/investor’s losses. However, as we move into the positive appreciation territory, we would expect struggling borrowers to have options to cure on their own, such as selling the home for the full amount of the loan or refinancing, so the borrowers may be less likely to seek modifications. The net effect of the borrowers’ and servicers’ incentives is consistent with the

²² The results pertain to house price appreciation since origination. We also experimented with recent house price appreciation (appreciation over the four quarters preceding the performance quarter) and the effects are consistent (similar significance levels and slightly lower magnitude)

flattening out of the relationship between the modification probability and appreciation rates across neighborhoods that have not lost value.

Loans on properties in neighborhoods that are greater than 60% black or greater than 40% Hispanic are more likely to be modified than loans on properties in other neighborhoods. One possible explanation is that foreclosure outreach efforts are targeted to primarily minority neighborhoods, which are thought to be more vulnerable to foreclosure.

Several findings suggest that servicers are less likely to modify loans of borrowers who the servicers fear may be especially likely to strategically default. Loans in neighborhoods with high educational attainment, for example, are less likely to be modified. Neighborhood educational attainment is likely to be a rough proxy for borrower educational attainment, and lenders may suspect that those borrowers may be more financially sophisticated and therefore more likely to strategically default. Loans in neighborhoods where many households have children also are less likely to be modified, which may reflect servicers' assumptions that those families are unlikely to actually walk away from their homes but may default strategically in order to reduce their payments through modifications. On the other hand, in neighborhoods with homeownership rates above 60% (a very high rate for New York City) borrowers are more likely to receive modifications. Other demographic characteristics, including the percentage of a neighborhood's population that is foreign-born, the percentage of its population over 65 years old, and its median household income, were not significant predictors of modification.

5.2 Determinants of Other Outcomes

Cure by borrower. In general our findings regarding the determinants of a borrower curing the delinquency themselves are consistent with prior literature. Borrowers who are more

financially stable (as indicated by higher FICO scores or FICO scores that have declined less) and live in neighborhoods whose residents have higher incomes and greater educational attainment, are more likely to cure the delinquency through their own actions, a sale or a refinance. Borrowers who took out loans that were less risky at origination – those with fixed rate, full documentation, lower relative interest rates, or lower current LTVs, and those without junior liens – also were more likely to cure their delinquencies themselves. Those findings may indicate that savvier borrowers may be able to refinance their loans or otherwise catch up on missed payments. Borrowers in neighborhoods with higher foreclosure rates in the 6 months prior to the loan month were less likely to cure on their own, possibly indicating that they had lost one of the options for curing: the ability to sell. Borrowers who received foreclosure counseling were less likely to cure on their own, but this may be a selection effect: borrowers may seek counseling only when they have run out of other options and cannot cure on their own.

Other non-liquidation workouts. We would expect the characteristics of borrowers coming to some sort of non-liquidation workout to be similar to borrowers who get modifications, and in many ways they are. The likelihood of coming to a non-liquidation workout decreases as relative interest rates rise. Although this runs contrary to the findings of Capozza and Thomson (2006), our data set covers multiple servicers--with great variability in outcomes across servicers--as well as both prime and non-prime loans and so our findings are more generalizable than theirs.

Similar to modified loans, borrowers with higher current FICO scores were less likely to get a non-liquidation workout than those with very low scores. Servicers may be loathe to offer workout options to borrowers with high FICO scores because they want to avoid rewarding otherwise financially healthy borrowers with workouts after strategic defaults.

There are two loan-related predictors of non-liquidation workouts that contrast with our modification findings: (1) loans guaranteed by GSEs are more likely to get a non-liquidation workout than those held in private securitization and (2) while adjustable rate loans were less likely to be modified than fixed rate loans, they are more likely to get another non-liquidation workout. The latter finding seems to indicate that although servicers may be wary to modify the riskier loans, they may be willing to pursue other, less extensive workouts perhaps in response to the strong criticism they face about these loans.

Servicer fixed effects are some of the strongest predictors of non-liquidation workouts in our model. 6 out of the 8 servicer dummy variables have statistically significant and quite large odds ratios with respect to non-liquidation workouts. There could be several reasons for this finding. First, the government efforts to make the loss mitigation process more uniform across servicers have focused more on modifications than on other alternative strategies. Second, servicers may differ in their institutional ability to offer workouts. And, third, the pool of loans that each servicer oversees may be systematically different and some servicers may have more loans in their portfolio that are better candidates for workouts for other reasons.

Borrowers receiving foreclosure counseling through one of the non-profit partners coordinated by the Center for New York City Neighborhoods were significantly more likely to obtain a non-liquidation workout than those who did not. So, even though we did not find that counseling had a significant effect on the likelihood that a borrower's loan would be modified, it does appear that foreclosure counseling helps borrowers to stay in their homes. However, it also may be true that borrowers who most want to stay in their homes are the ones seeking out foreclosure counseling, and hence, there is probably some self-selection bias here.

Liquidation. Our findings on the likelihood that a servicer will complete foreclosure of a property through liquidation support some of the findings of prior research. We found little difference in the liquidation rate based on the race or ethnicity of the borrowers, affirming the descriptive findings of Ambrose and Capone (1996). In neighborhoods with positive price appreciation (since loan origination), we found servicers more likely to liquidate the property when the appreciation rate is higher, whereas in neighborhoods which have lost value, servicers are less likely to liquidate when the depreciation rate is lower.²³ In addition, we find that loans guaranteed by the GSEs are less likely to be liquidated. We also find that investor owned properties are more likely to be liquidated, which follows conventional wisdom. Borrowers with FICO score that declined from origination to delinquency were more likely to have their property liquidated. A FICO score that already declined prior to the delinquency probably indicates that the borrower was suffering from financial hardship beyond just the cost of the mortgage payments. Such borrowers were probably not good candidates for modifications or other non-liquidation workouts. Loans on properties in neighborhoods with higher concentrations of non-Hispanic blacks or Hispanics are less likely to be liquidated than loans on properties in neighborhoods with lower percentages of such minorities. We also found that loans in neighborhoods with higher percentages of foreign-born or high educational attainment are less likely to be liquidated, although these differences are statistically significant only at the 10 percent level. As community district unemployment rates increased in the year prior to the loan-month being studied, the likelihood of liquidation increased. Liquidation was the only outcome for which the change in the unemployment rate had a significant effect in our model, albeit at the 10% level. As with non-liquidation workouts, servicer fixed effects are very strong predictors of liquidation, with 6 out of the 8 servicer indicators having statistically significant and large odds

²³ Note, however that these effects are statistically significant only at the 10 percent level.

ratios with respect to this outcome. Finally, the borough fixed effects in our model indicate that properties in Queens are significantly more likely to be liquidated than properties in the other boroughs, probably because properties in Queens that are liquidated spend less time from *lispens* to liquidation.

Sensitivity Analysis. Because we focused our analysis on New York City, for which much detailed data is available, we were able to include both variables that are not available in national models (foreclosure counseling, borrowers' race and the presence of a junior lien) and variables that have not been used in national models before but that could be added (neighborhood foreclosure rate and neighborhood house price appreciation). As Table 4 shows, our fully controlled model is a slightly better fit for explaining the incidence of modifications than the models that have fewer controls. However, with few exceptions, all of the variables in the fully controlled model point in the same direction and have similar magnitudes as in the leaner models. The one stark exception is the neighborhood racial composition. In the simplest model, borrowers in black and Hispanic neighborhoods appear to be less likely to cure the delinquency on their own. However, when we add in the neighborhood 6-month prior foreclosure rate and neighborhood house price appreciation, these differences disappear.

6. Conclusion

The rich data set used in this paper allowed us to improve on the existing literature by assessing the impact that loan, servicer, borrower and neighborhood characteristics have on the outcome of a seriously delinquent loan. The OCC's MortgageMetrics data allowed us to pay particular attention to the determinants of loan modifications. Although our work is limited to the context of New York City, we believe our results may be generalizable to many other areas.

Manhattan may be a fairly unique housing market, but the majority of the mortgages we examine were originated in the other boroughs, which are similar in density, housing stock, and other measures to many other cities across the country. For example, most foreclosures in the city have taken place in the outer borough neighborhoods with a high concentration of one- and two-family housing, and most of the homes affected by foreclosure are one- to four- family homes. More importantly perhaps, we can not think of strong reasons why the more distinct economic environment of New York City would affect the relationships between loss mitigation outcomes and their determinants.²⁴ Indeed, our analysis on New York City confirms the basic findings with respect to the relatively narrow set of variables used in national-level analyses, even when controlling for data which are difficult to incorporate or have not been previously used in national models.

We find that both borrowers and servicers appear to be acting to minimize their (or their lender/investors') losses in their propensity to cure, modify, come to another non-liquidation workout or liquidate the property. As we would expect, current LTV is one of the strongest and most statistically significant predictors of either cure or modification, with the likelihood of curing falling and the likelihood of modifications rising as the LTV rises. Our evidence suggests that borrowers who live in highly educated, high income neighborhoods and have high credit scores or FICO scores that have declined less since loan origination are likely to find a way to cure on their own.

The neighborhood's housing price appreciation also is a strong predictor of outcomes. Our findings suggest that servicers may be wary of offering modifications and more likely to liquidate the loan in neighborhoods with high house price depreciation rates because those

²⁴ Housing and labor market variables may have smaller variation in the stronger housing and labor markets of New York City, however this would only affect the precision of the coefficients on those variables.

neighborhoods may have little chance of recovering in the short term. We also find that in neighborhoods with positive appreciation, the servicers are more likely to foreclose the higher the appreciation rate, perhaps because they expect to sell the property quicker and/or at higher price through a foreclosure auction or resale and thus profit from (or lose less from) the foreclosure.

Especially risky loan characteristics, including junior liens, ARMs, interest only loans, very high interest rate loans and loans without full documentation result in bad outcomes for both the borrowers and the servicers. Unsurprisingly, having any of these high risk (and now relatively unavailable) characteristics on a loan made a borrower less likely to be able to cure the default on their own. Most of these characteristics also made it less likely that a loan would be modified, either because the cost of modification would be too high for the most exotic loans (such as interest only) or because the actual process of modifying is more difficult, as in the case of junior liens that would require coordination with another servicer or in the case of loans originated without the full documentation necessary to complete a modification.

Additional evidence that servicers are acting to minimize lender's or investors' losses in their modification decisions can be gleaned from the finding that adjustable rate loans are more likely to be modified immediately prior to or following the initial rate adjustment than many months after the rate adjustment. As more time passes from adjustment, a borrower's delinquency likely has less to do with the payment shock at adjustment and more to do with some unobserved financial difficulty such as the loss of a job. Taking this into account, it appears that servicers are modifying loans when the borrower could afford payments were it not for the payment shock of the adjustment.

We find no evidence that servicers are discriminating by race in their decisions about whether to modify loans, offer other workouts, or foreclose. In this analysis, we cannot, however, rule out the possibility that the terms of modifications or other workouts might differ by race or some other characteristics of borrowers. Although an individual borrower's race is not a good predictor of the outcome of delinquency, the race of the neighborhood in which the property is located is a good predictor of loan modifications and liquidations. Our model includes controls for many demographic characteristics of a neighborhood, as well as the recent foreclosure rate in the neighborhood, but even controlling for those factors, neighborhoods with large shares of black and Hispanic residents are *more* likely to get modifications and to avoid foreclosure. This could be because foreclosure prevention efforts are concentrated in minority neighborhoods. Although we find that foreclosure counseling does not significantly increase the likelihood of a loan being modified, it does have a significant and positive effect on the likelihood of the borrower and servicer agreeing on some other workout.

Finally, servicers do not vary considerably in their grants of modifications, however there is significant variation in their propensity to offer other non-liquidation workouts and to pursue liquidation. These findings may be due, at least in part, to the fact that the government efforts to make the loss mitigation process more uniform across servicers have focused, so far, more on modifications than on other alternative strategies. They may also reflect some unobservable factors about the loans or staffing, training, or incentive differences among servicers.

Our study suggests that modification programs may need to be refined in several ways. First, modification programs should learn from counseling programs. We find that borrowers who receive counseling services are more likely to come to some sort of workout agreement with the servicer, but are no more likely to have their loan be formally modified. If this is because

none of the currently available modification programs are a good fit for these borrowers, then the modification programs should be revised accordingly.

Further, we found that local house price dynamics are a good predictor of whether a loan will be modified. Although the Furman Center neighborhood level repeat sales indices in New York City are more detailed than indices available in other areas, there are opportunities to include house price dynamics in the criteria to determine eligibility for a modification. Case-Shiller constructs zip code level house price appreciation indices for purchase and makes tiered indices available at the MSA level without charge.

Finally, our findings suggest a need for additional attention to certain servicers. Even controlling for characteristics of the loan, borrower, property and neighborhood, servicers have pursued liquidations and non-liquidation workouts other than modifications at wildly different rates. This suggests that some servicers may need additional incentives to avoid liquidation or need more time and assistance to build the capacity to do so.

We plan to extend this study by analyzing the default rate and determinants of outcomes for borrowers who have gotten modifications. That extension will reveal what characteristics of a modification will most likely predict success while controlling for characteristics of the borrower, the neighborhood and the original loan.

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18

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Appendix

Evolution of Loan Modification Policies

August 2007: The Bush Administration announces the FHASecure refinancing program for borrowers delinquent on their adjustable rate mortgages or current on fixed or adjustable rate mortgages. The program offered borrowers the option to refinance into a traditional, fixed rate, FHA guaranteed loan. The program required proof of a dependable income and the ability to make future mortgage payments. FHASecure was ended in December 2008 and only refinanced about 4,000 loans.

October 10th, 2007: the US Treasury Department and the U.S. Department of Housing and Urban Development (HUD) announces the HOPE NOW initiative to help homeowners avoid foreclosure. HOPE NOW consists of mortgage servicers, mortgage insurers, GSEs, non-profits, mortgage-related trade associations and mortgage counselors, and seeks to coordinate the efforts of those organizations to keep homeowners in their homes. HOPE NOW helps distressed homeowners to communicate with their servicers in order to negotiate home modifications.

July, 2008: Congress authorizes the Federal Housing Administration (FHA) under the Housing and Economic Recovery Act (HERA) to insure up to \$300 billion in loans through a new program, HOPE for Homeowners. This program required existing lenders to accept as payment in full of the original first lien mortgage an amount equal to no more than 90 percent of the current appraised value of the property (87 percent after payment of the upfront premium to

FHA)—a substantial principal write-down in many cases. Hope for Homeowners was voluntary for both borrowers and lenders, and resulted in very few modifications.

November 11th, 2008: The Federal Housing Finance Agency announces a new streamlined loan modification program, modeled largely on the FDIC's IndyMac protocol (IndyMac was a mortgage company taken over by the FDIC). The program encourages servicers to restructure loans for eligible borrowers so that monthly mortgage payments are no more than 38% of a borrower's monthly gross income. Servicers can reduce monthly mortgage payments by lowering the interest rate, extending the life of the loan, deferring the payment of some of the principal, or a mix of these actions. Eligible loans include Fannie Mae and Freddie Mac loans along with portfolio loans by participating servicers. Borrowers under this program must be at least 90 days delinquent, owe more than 90% of the value of their homes, must have not filed for bankruptcy, and must certify that they are suffering some sort of economic hardship. Servicers are awarded \$800 by the government for each loan that they modify.

February 18th, 2009: The Obama administration announces the Homeowner Affordability and Stability Plan, which includes a plan to help financially distressed homeowners. Two weeks later, the details of this plan, the Making Home Affordable (MHA) plan, are announced. MHA has many components, including the Home Affordable Refinance Program (HARP), the Home Affordable Unemployment Program (UP), the Second Lien Modification Program (2MP), and the Home Affordable Foreclosure Alternatives Program (HAFA). The key component of MHA regarding loan modifications, however, is the Home Affordable Modification Program (HAMP). . HAMP provides a streamlined structure for modifications and financial incentives for servicers

to modify loans. The program requires that servicers reduce monthly payments to 38% of gross monthly income, after which Treasury will match the servicer dollar-for-dollar for the cost of further reducing the monthly payment to 31% of gross income. Servicers also receive an upfront payment of \$1,000 for each modification, and a further \$1,000 per year for three years if the borrower remains in the HAMP program.

In order to receive a modification under HAMP, a borrower must meet the following conditions: (1) the property must be owner-occupied and the borrower's primary residence, (2) the property must be a single-family property with a maximum unpaid principal balance of \$729,750 or less, (3) the loan must have originated on Jan. 1, 2009 or before, and (4) the monthly payment must be more than 31% of the homeowner's gross monthly income.

If a borrower is eligible, a servicer will adjust the monthly mortgage payment to 31% of a borrower's total monthly income by first reducing the interest rate to as low as 2%, then if necessary, extending the loan term to 40 years, and finally, if necessary, forbearing a portion of the principal until the loan is paid off and waiving interest on the deferred amount.

If these conditions are met, a servicer will then apply a Net Present Value (NPV) test to determine whether the value of the loan to the investor will be greater if the loan is modified (<http://makinghomeaffordable.gov/borrower-faqs.html#18>). The incentives provided by HAMP will be included in this figure. If the modified loan is worth more than the loan without the modification, the servicer is required to provide the modification on a (usually three month) trial basis (<http://makinghomeaffordable.gov/borrower-faqs.html#18>). If the modified loan is not worth more than the loan in its original state, it is at the servicer's discretion whether to modify the loan.

The purpose of the trial period is to provide immediate relief for the borrower while providing a check that the modification is sustainable for the borrower and that the borrower indeed meets the qualification requirement of HAMP. If the borrower makes timely payments for the duration of the trial period and no problems are found with the borrower's financial information, the servicer will execute a permanent modification. The modified rate will remain constant for the first five years, and then can only increase 1% until it reaches whatever the market rate was at the time the modification was set.

As a part of the Helping Families Save Their Homes Act of 2009, HAMP also now covers FHA loans under a sub-program, FHA-HAMP, which combines a loan modification with a partial claim, which is a one-time loan offered only in conjunction with FHA loans to help borrowers get current on their loans by repaying past due interest and escrow. Like the rest of HAMP, FHA-HAMP covers homeowners in default as well as homeowners facing imminent default, and requires a three-month trial period.

May 20th, 2009: President Obama signs the Helping Families Save Their Homes Act of 2009. The act was originally intended to allow bankruptcy judges to modify the principals of mortgages in bankruptcy courts, but that provision was eliminated from the bill before passage by Congress. The legislation increases legal protections for servicers against lawsuits by investors, and it allows FHA lenders to make more significant modifications for FHA loans.

Table 1. Descriptive Statistics**A. Outcomes of Seriously Delinquent Loans**

Outcome	% of all loans
Cure	15.0
Modification	9.4
Other Workout	8.5
- Repayment Plan	1.3
- FHA Partial Claim	0.5
- Forbearance Plan	0.3
- Other	6.3
- Reaged/Deferred/Extended	0.2
Liquidation	5.6
Delinquency Continues	61.5

B. Loan Characteristics

Variable	Mean
Credit Class	
Prime	0.496
Non-Prime	0.433
(missing credit class indicator)	0.071
Product Description	
FRM	0.604
ARM 2/28	0.134
ARM 3/27	0.049
ARM (other)	0.186
Other	0.027
ARM * Margin at Origination ¹	2.203
(ARM * missing margin at origination indicator) ²	0.370
Interest Only at Origination	0.197
(missing interest only indicator)	0.060
Full Documentation	0.349
(missing full documentation indicator)	0.010
Product Group	
Government (FHA, VA)	0.066
Conventional with PMI	0.128
Conventional	0.780
Other	0.026
Loan Purpose	
Home Purchase	0.430
Refinance	0.350
Home Improvement	0.019
(missing loan purpose indicator)	0.201
Relative interest rate at origination (FRMs): ³	
<0	0.207
0-1	0.423
1-2	0.149
2-3	0.036
>3	0.017

	(missing interest rate indicator)	0.168
Relative interest rate at origination (ARMs): ²		
	<0	0.104
	0-2	0.308
	2-4	0.481
	4-6	0.090
	>6	0.009
	(missing interest rate indicator)	0.008
Debt-to-income at origination		
	<45%	0.360
	45-50%	0.106
	>50%	0.130
	(missing DTI indicator)	0.404
Investor type		
	Private Investor	0.451
	GSE	0.352
	Held in Portfolio	0.161
	(missing investor type indicator)	0.037
Percentage of outstanding loans in neighborhood serviced by the servicer		0.185
log (Current Unpaid Balance)		12.902
Number of months post-adjustment (ARMs): ²		
	before 1st adjust or no adjust	0.589
	0-3	0.071
	4-6	0.058
	>6	0.282
Loan Age (months)		31.843
Default Time (months)		7.689
Current LTV	Mean	1.018
	<80%	0.171
	80-100%	0.255
	100-120%	0.209
	>120%	0.211
	(missing LTV indicator)	0.154
LTV increase between origination and current month ^{4,5}		0.243
	(missing LTV increase indicator)	0.155
Has a Junior Lien on the Property		0.330
Number of Loans		29,366
Number of Loan-Months		258,326

C. Borrower and Property Characteristics

Variable	Mean	
Owner Occupier	0.885	
Property Type		
	Single Family or Condo	0.431
	2-4 Family	0.548
	5+ Family	0.020
Borrower Race/Ethnicity		
	Non-Hispanic Black	0.272
	Non-Hispanic Asian	0.085

	Non-Hispanic Other	0.012
	Non-Hispanic White	0.160
	Hispanic	0.142
	(missing race/ethnicity indicator)	0.328
Received Foreclosure Counseling ⁶		0.022
Current FICO Score ⁴	Mean	556.530
	<560	0.528
	560-620	0.244
	620-650	0.062
	650-680	0.038
	680-720	0.028
	>720	0.025
	(missing FICO score indicator)	0.074
FICO Score decline between origination and current month ⁴		111.107
	(missing FICO Score decline indicator)	0.141
Number of Loans		29,366
Number of Loan-Months		258,326

D. Neighborhood Characteristics

Variable	Estimation Sample NYC (4 boroughs)	
	Mean	Mean
<i>Neighborhood Racial Composition</i>		
% Non-Hispanic Black		
	<20%	0.388
	20-40%	0.093
	40-60%	0.086
	60-80%	0.143
	>80%	0.290
% Hispanic		
	<20%	0.620
	20-40%	0.200
	>40%	0.180
% Non-Hispanic Asian		
	<20%	0.882
	20-40%	0.101
	>40%	0.017
<i>Other Neighborhood Characteristics</i>		
% Foreign Born		
	<20%	0.138
	20-40%	0.456
	40-60%	0.328
	>60%	0.078
% >65 Years Old		
	<10%	0.496
	10-20%	0.458
	>20%	0.046
% of households with Children		
	<25%	0.087
	25-50%	0.837

	>=50%	0.076	0.049
Median Household Income (1999)			
	<\$20,000	0.058	0.121
	\$20,000-40,000	0.412	0.435
	\$40,000-60,000	0.443	0.312
	>\$60,000	0.088	0.132
% of adults with a Bachelor's degree or higher			
	<20%	0.656	0.530
	20-40%	0.288	0.309
	40-60%	0.036	0.082
	>60%	0.020	0.079
Homeownership Rate			
	<20%	0.170	0.333
	20-40%	0.266	0.312
	40-60%	0.246	0.182
	>60%	0.318	0.173
Origination Year			
	2004	0.093	
	2005	0.195	
	2006	0.333	
	2007	0.283	
	2008	0.095	
Borough			
	Manhattan	0.029	
	Bronx	0.135	
	Brooklyn	0.330	
	Queens	0.506	
Quarter of Loan Performance			
	2008 - 1	0.057	
	2008 - 2	0.095	
	2008 - 3	0.090	
	2008 - 4	0.104	
	2009 - 1	0.130	
	2009 - 2	0.147	
	2009 - 3	0.172	
	2009 - 4	0.205	
Crime Rate		0.034	
Change in Unemployment Rate		0.021	
Recent Foreclosure Rate			
	<1%	0.281	
	1-2%	0.268	
	2-3%	0.215	
	>3%	0.236	
Positive HP Appreciation		0.115	
HP Appreciation		-0.193	
Number of Loans		29,366	
Number of Loan-Months		258,326	

E. Servicer Characteristics: Mean FICO and LTV at Origination ⁴

Servicer	FICO	LTV
1	656.1	0.800
2	684.1	0.451
3	667.2	0.755
4	661.7	0.757
5	685.8	0.740
6	697.8	0.784
7	671.6	0.772
8	662.9	0.701
9	688.2	0.761
10	671.7	0.765
11	659.7	0.740

Notes

Statistics based on the loan-month-level sample are represented with gray shading. The other statistics are based on the loan-level sample.

- 1) The mean is computed using only the ARMs with non-missing margin
- 2) The means are computed using only the ARMs
- 3) The means are computed using only the FRMs
- 4) The mean is computed using only non-missing values
- 5) This variable and its missing value indicator are not included in regressions due to high correlation with the house price appreciation.
- 6) Although this variable varies with the loan-month, the mean is computed at the loan level and thus represents the share of borrowers who received counseling before the default resolution occurred (or before the end of the study period if no resolution was reached).

Table 2. Characteristics of Loans Modified Before and After Becoming 60+DPD

Variable	Modified Before	Modified After	Absolute Difference in Means
	Becoming 60+ DPD	Becoming 60+ DPD (used in our analysis)	
N	866	2769	
Relative interest rate at origination (FRMs) ¹			
<0	0.430	0.286	0.144
0-1	0.307	0.204	0.103
1-2	0.152	0.101	0.051
2-3	0.054	0.036	0.018
>3	0.022	0.015	0.007
(missing interest rate indicator)	0.035	0.023	0.012
Relative interest rate at origination (ARMs) ²			
<0	0.162	0.228	0.066
0-2	0.325	0.458	0.133
2-4	0.424	0.596	0.173
4-6	0.071	0.100	0.029
>6	0.005	0.008	0.002
(missing interest rate indicator)	0.013	0.018	0.005
Investor type			
Private Investor	0.661	0.569	0.092
GSE	0.102	0.228	0.127
Held in Portfolio	0.225	0.181	0.044
(missing investor type indicator)	0.013	0.022	0.009
Product Group			
Government (FHA, VA)	0.008	0.082	0.074
Conventional with PMI	0.124	0.164	0.040
Conventional	0.818	0.710	0.108
Other	0.051	0.044	0.007
Product Description			
Fixed	0.365	0.549	0.184
ARM 2/28	0.182	0.101	0.081
ARM 3/27	0.129	0.056	0.073
ARM (other)	0.263	0.199	0.064
Other	0.060	0.094	0.034
ARM * Margin at Origination ³	2.727	2.789	0.062
(ARM * missing margin at origination indicator)	0.669	0.479	0.190
Interest Only at Origination	0.187	0.138	0.049
(missing interest only indicator)	0.064	0.119	0.055
Full Documentation	0.421	0.399	0.022
(missing full documentation indicator)	0.031	0.016	0.016
Credit Class			
Prime	0.236	0.288	0.053
Non-Prime	0.725	0.619	0.107
(missing credit class indicator)	0.039	0.093	0.054

Notes:

- 1) The means are computed using only the FRMs
- 2) The means are computed using only the ARMs
- 3) The mean is computed using only the ARMs with non-missing margin

Table 3. Multinomial Logistic Regression Results for Determinants of Outcomes (Odds Ratio Estimates)

Variable	Odds Ratio ¹			
	Cure	Modification	Other Workout	Liquidation
Credit Class Non-Prime	0.975	1.759***	0.947	0.905
(missing credit class indicator)	0.703***	0.781**	0.692***	1.639***
Product Description [REF: FRM]				
ARM 2/28	0.416***	0.220***	1.25	1.098
ARM 3/27	0.636**	0.246***	1.476**	1.051
ARM (other)	0.915	0.359***	1.426**	1.124
Other	1.008	1.057	1.510***	0.905
ARM * Margin at Origination	1.017	1.034	0.967	0.987
(ARM * missing margin at origination indicator)	0.706***	0.821*	0.691***	1.293**
Interest Only at Origination	0.868**	0.674***	0.933	1.022
(missing interest only indicator)	0.814**	1.142	0.844*	1.194
Full Documentation	1.241***	1.229***	1.093	0.884
(missing full documentation indicator)	1.772***	0.822	0.216***	1.199
Product Group [REF: Conventional]				
Government (FHA, VA)	0.898	0.935	1.038	0.737
Conventional with PMI	1.029	1.115	0.875	0.894
Other	1.141	0.945	0.357**	0.958
Loan Purpose [REF: Home Improvement]				
Home Purchase	0.951	0.912	1.003	0.993
Refinance	1.167	1.049	1.214	0.673*
(missing loan purpose indicator)	0.95	0.907	1.221	0.738
Relative interest rate at origination (FRMs) [REF: <0]				
0-1	0.771***	0.363***	0.904	1.245
1-2	0.618***	0.310***	0.809**	1.275
2-3	0.497***	0.360***	0.424***	2.400***
>3	0.269***	0.216***	0.188**	1.259
(missing interest rate indicator)	0.744***	0.309***	0.745***	0.756
Relative interest rate at origination (ARMs) [REF: <0]				
0-2	0.869	1.487***	0.667***	0.935
2-4	0.801**	1.002	0.530***	0.946
4-6	0.772*	1.314*	0.393***	1.051
>6	0.548*	0.543	0.000***	1.03
(missing interest rate indicator)	0.556	0.807	0.374***	0.336
Number of months post-adjustment (ARMs) [REF: <0]				
0-3	1.136	1.257*	1.135	1.292*
4-6	1.042	0.532***	0.968	1.178
>6	1.192	0.256***	1.015	1.303**
Debt-to-income at origination [REF: <45%]				
45-50%	0.983	1.238***	0.833	1.242*
>50%	0.941	1.004	1.114	1.092
(missing DTI indicator)	1.075	1.224***	0.829**	1.343***
Investor type [REF: Private Investor]				
GSE	1.111**	0.672***	2.003***	0.712***
Held in Portfolio	0.937	1.260***	1.710***	1.033
(missing investor type indicator)	1.039	0.742**	1.242***	5.893***
Current LTV [REF: <80%]				
80-100%	0.712***	1.578***	1.029	1.147
100-120%	0.621***	2.182***	1.036	1.037
>120%	0.623***	2.668***	1.123	1.012
(missing LTV indicator)	0.779***	1.461***	2.035***	3.297***
Has a Junior Lien on the Property	0.860***	0.863***	0.957	0.943
log (Current Unpaid Balance)	0.526***	1.119*	0.905	0.884

Loan Age	1.011**	1.017***	0.997	0.982**
Default Time	0.843***	0.986***	0.913***	1.183***
Percentage of outstanding loans in neighborhood serviced by the servicer	2.090*	1.452	1.479	1.508
Borrower and Property Characteristics				
Owner Occupier	0.916	1.245***	1.302***	0.807***
Property Type [REF: Single Fam & Condo]				
2-4 Family	0.95	0.877***	0.94	0.984
5+ Family	0.869	0.652**	1.16	0.969
Current FICO Score [REF: <560]				
560-620	0.987	0.814***	0.757***	1.272***
620-650	1.129*	0.568***	0.685***	1.254*
650-680	1.212**	0.502***	0.517***	0.887
680-720	1.15	0.403***	0.653***	0.897
>720	1.207**	0.476***	0.716**	1.178
(missing FICO score)	1.337***	0.576***	0.663**	5.192***
FICO Score decline between origination and delinquency	0.997***	0.996***	0.998***	1.002***
(missing FICO Score decline indicator)	0.688***	0.709***	0.683***	0.717**
Borrower Race/Ethnicity [REF: Non-Hispanic White]				
Non-Hispanic Black	0.921	0.926	1.077	1.106
Non-Hispanic Asian	0.899	0.841*	1.101	1.098
Non-Hispanic Other	0.743*	0.751	1.212	1.667**
Hispanic	0.775***	0.902	0.941	1.201*
(missing race/ethnicity)	0.976	0.97	0.991	1.037
Received Foreclosure Counseling	0.480***	1.234	1.502***	0.578
Neighborhood Characteristics				
Recent Foreclosure Rate [REF: <1]				
1-2%	0.820***	0.850***	0.974	1.055
2-3%	0.735***	0.857**	0.954	1.041
>3%	0.699***	0.762***	0.867*	1.013
Positive HP Appreciation	0.961	0.991	1.069	1.185
Positive HP Appreciation * HP Appreciation	1.017	1.043	0.591	3.494*
Negative HP Appreciation * HP Appreciation	0.795	5.553***	1.363	0.492*
<i>Neighborhood Racial Composition [REF: 0-20%]</i>				
% Non-Hispanic Black				
20-40%	0.9	1.112	0.94	0.9
40-60%	0.954	1.152	1.009	0.801*
60-80%	0.943	1.457***	0.999	0.754**
>80%	0.972	1.335***	1.04	0.653***
% Hispanic				
20-40%	0.887**	1.039	1.113	0.810**
>40%	0.956	1.254**	1.023	0.740**
% Non-Hispanic Asian				
20-40%	1.094	0.883	0.958	1.054
>40%	1.117	0.885	1.235	1.418
% Foreign Born [REF: 0-20%]				
20-40%	0.923	1.054	0.922	0.963
40-60%	0.939	1.081	1.007	0.831*
>60%	0.942	0.97	0.917	0.759*
% >65 Years Old [REF: 0-10%]				
10-20%	0.98	1	1.07	1.009
>20%	0.993	0.788*	0.819	0.774
% of households with Children [REF: 0-25%]				
25-50%	0.890*	0.781***	0.923	1.171
>=50%	0.829*	0.743**	0.877	1.172
Median Household Income (1999) [REF: 0-\$20,000]				
\$20,000-40,000	1.201**	0.903	1.057	0.912

	\$40,000-60,000	1.312***	0.978	1.068	0.864
	>\$60,000	1.346**	0.962	1.395**	0.854
<hr/>					
% of adults with a Bachelor's degree or higher [REF: 0-20%]					
	20-40%	1.110**	1.053	0.936	0.895
	40-60%	1.293***	0.836	0.905	1.093
	>60%	1.16	0.572**	0.932	0.447*
<hr/>					
Homeownership Rate [REF: 0-20%]					
	20-40%	0.932	1.029	0.870*	0.932
	40-60%	0.839***	1.144	1.02	0.989
	>60%	0.899	1.269**	0.957	0.93
<hr/>					
Crime Rate					
		1.761**	1.975***	0.258	1.031
<hr/>					
Change in Unemployment Rate					
		1.106	1.904	0.449	14.727*
<hr/>					
Origination year [REF: 2004]					
	2005	1.123	1.377***	1.103	1.364*
	2006	0.962	1.141	0.94	1.051
	2007	1.052	1.283	0.805	0.661
	2008	1.005	0.964	0.627	0.734
<hr/>					
Borough [REF: Manhattan]					
	Bronx	0.658***	1.23	0.998	1.028
	Brooklyn	0.691***	0.973	0.871	0.837
	Queens	0.588***	1.072	0.959	2.218***
<hr/>					
Quarter of Loan Performance [REF: 2008 - 1]					
	2008 - 2	1.152**	1.695***	1.481***	1.406**
	2008 - 3	1.198**	1.575***	1.058	1.189
	2008 - 4	1.027	1.309*	0.897	0.715*
	2009 - 1	0.803*	1.774***	0.723	0.656
	2009 - 2	0.614***	1.105	1.262	0.628*
	2009 - 3	0.630***	0.946	1.435*	0.633
	2009 - 4	0.504***	1.318	0.839	0.484**
<hr/>					
Servicer fixed effects included					
<hr/>					
Pseudo-R2	0.1379				
N	258,326				

Notes:

1) The reference outcome for the odds ratio computation is "Delinquency Continues"

*** denotes results that are statistically significant at the 1 percent level

** denotes results that are statistically significant at the 5 percent level

* denotes results that are statistically significant at the 10 percent level

GSE	1.111**	0.672***	2.003***	0.712***	1.115**	0.672***	2.005***	0.711***	1.115**	0.667***	2.004***	0.710***
Held in Portfolio	0.937	1.260***	1.710***	1.033	0.94	1.266***	1.718***	1.034	0.935	1.272***	1.721***	1.03
(missing investor type indicator)	1.039	0.742**	1.242***	5.893***	1.057	0.754**	1.238**	5.880***	1.051	0.767*	1.240***	5.864***
Current LTV [REF: <80%]												
80-100%	0.712***	1.578***	1.029	1.147	0.705***	1.569***	1.025	1.147	0.708***	1.415***	0.996	1.072
100-120%	0.621***	2.182***	1.036	1.037	0.614***	2.187***	1.034	1.047	0.622***	1.707***	0.973	1.056
>120%	0.623***	2.668***	1.123	1.012	0.614***	2.681***	1.13	1.026	0.627***	1.781***	1.023	1.119
(missing LTV indicator)	0.779***	1.461***	2.035***	3.297***	0.777***	1.456***	2.032***	3.300***	0.777***	1.319***	1.981***	3.260***
Has a Junior Lien on the Property	0.860***	0.863***	0.957	0.943								
log (Current Unpaid Balance)	0.526***	1.119*	0.905	0.884	0.520***	1.108	0.904*	0.883	0.516***	1.168**	0.915	0.878
Loan Age	1.011**	1.017***	0.997	0.982**	1.010**	1.016**	0.997	0.981**	1.009*	1.020***	0.997	0.982**
Default Time	0.843***	0.986***	0.913***	1.183***	0.843***	0.986***	0.913***	1.183***	0.842***	0.985***	0.912***	1.183***
Percentage of outstanding loans in neighborhood serviced by the servicer	2.090*	1.452	1.479	1.508	2.065*	1.377	1.506	1.57	2.130*	1.181	1.444	1.481

Borrower and Property Characteristics

Owner Occupier	0.916	1.245***	1.302***	0.807***	0.902*	1.237***	1.304***	0.810***	0.900*	1.252***	1.308***	0.809***
Property Type [REF: Single Fam & Condo]												
2-4 Family	0.95	0.877***	0.94	0.984	0.947	0.874***	0.939	0.988	0.936*	0.848***	0.932	0.991
5+ Family	0.869	0.652**	1.16	0.969	0.892	0.661**	1.162	0.976	0.902	0.659**	1.158	0.976
Current FICO Score [REF: <560]												
560-620	0.987	0.814***	0.757***	1.272***	0.984	0.812***	0.757***	1.264***	0.982	0.817***	0.756***	1.266***
620-650	1.129*	0.568***	0.685***	1.254*	1.121*	0.566***	0.687***	1.241*	1.121*	0.570***	0.687***	1.245*
650-680	1.212**	0.502***	0.517***	0.887	1.199**	0.497***	0.514***	0.885	1.203**	0.503***	0.514***	0.887
680-720	1.15	0.403***	0.653***	0.897	1.137	0.400***	0.651***	0.893	1.133	0.403***	0.650***	0.893
>720	1.207**	0.476***	0.716**	1.178	1.198*	0.471***	0.714**	1.185	1.201*	0.479***	0.714**	1.186
(missing FICO score)	1.337***	0.576***	0.663**	5.192***	1.333***	0.574***	0.663**	5.188***	1.324***	0.579***	0.661**	5.158***
FICO Score decline between origination and delinquency	0.997***	0.996***	0.998***	1.002***	0.997***	0.996***	0.998***	1.002***	0.997***	0.996***	0.998***	1.002***
(missing FICO Score decline indicator)	0.688***	0.709***	0.683***	0.717**	0.682***	0.704***	0.679***	0.711**	0.680***	0.704***	0.678***	0.718**
Borrower Race/Ethnicity [REF: Non-Hispanic White]												
Non-Hispanic Black	0.921	0.926	1.077	1.106								
Non-Hispanic Asian	0.899	0.841*	1.101	1.098								
Non-Hispanic Other	0.743*	0.751	1.212	1.667**								
Hispanic	0.775***	0.902	0.941	1.201*								
(missing race/ethnicity)	0.976	0.97	0.991	1.037								
Received Foreclosure Counseling	0.480***	1.234	1.502***	0.578								

Neighborhood Characteristics

Recent Foreclosure Rate [REF: <1]												
1-2%	0.820***	0.850***	0.974	1.055	0.814***	0.848***	0.978	1.06				
2-3%	0.735***	0.857**	0.954	1.041	0.731***	0.854**	0.958	1.046				
>3%	0.699***	0.762***	0.867*	1.013	0.692***	0.759***	0.871*	1.017				
Positive HP Appreciation	0.961	0.991	1.069	1.185	0.962	0.988	1.07	1.184				
Positive HP Appreciation * HP Appreciation	1.017	1.043	0.591	3.494*	1.009	1.059	0.588	3.456*				
Negative HP Appreciation * HP Appreciation	0.795	5.553***	1.363	0.492*	0.794	5.693***	1.368	0.501*				

Neighborhood Racial Composition [REF: 0-20%]

% Non-Hispanic Black 20-40%	0.9	1.112	0.94	0.9	0.894*	1.102	0.955	0.906	0.856**	1.066	0.944	0.926
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	40-60%	0.954	1.152	1.009	0.801*	0.95	1.151	1.037	0.795*	0.860**	1.06	1.001	0.809*
	60-80%	0.943	1.457***	0.999	0.754**	0.931	1.444***	1.024	0.749**	0.810***	1.260***	0.978	0.767**
	>80%	0.972	1.335***	1.04	0.653***	0.964	1.322***	1.068	0.649***	0.830***	1.119	1.014	0.672***
% Hispanic	20-40%	0.887**	1.039	1.113	0.810**	0.869**	1.023	1.111	0.826**	0.852***	0.967	1.103	0.842*
	>40%	0.956	1.254**	1.023	0.740**	0.905	1.232**	0.997	0.756**	0.840**	1.112	0.971	0.778**
% Non-Hispanic Asian	20-40%	1.094	0.883	0.958	1.054	1.085	0.865	0.967	1.053	1.111*	0.866	0.97	1.052
	>40%	1.117	0.885	1.235	1.418	1.106	0.852	1.258	1.421*	1.152	0.92	1.277	1.393
% Foreign Born [REF: 0-20%]													
	20-40%	0.923	1.054	0.922	0.963	0.92	1.055	0.926	0.97	0.916	1.08	0.932	0.968
	40-60%	0.939	1.081	1.007	0.831*	0.933	1.079	1.02	0.841	0.937	1.124	1.036	0.841
	>60%	0.942	0.97	0.917	0.759*	0.931	0.958	0.931	0.767*	0.927	0.987	0.949	0.773*
% >65 Years Old [REF: 0-10%]													
	10-20%	0.98	1	1.07	1.009	0.98	1.002	1.065	1.007	0.999	1.017	1.071	1.005
	>20%	0.993	0.788*	0.819	0.774	0.993	0.791*	0.818	0.767	1.034	0.809*	0.822	0.746
% of households with Children [REF: 0-25%]													
	25-50%	0.890*	0.781***	0.923	1.171	0.886*	0.779***	0.922	1.185	0.877**	0.763***	0.917	1.182
	>=50%	0.829*	0.743**	0.877	1.172	0.826**	0.741**	0.874	1.178	0.788**	0.702***	0.855	1.177
Median Household Income (1999) [REF: 0-\$20,000]													
	\$20,000-40,000	1.201**	0.903	1.057	0.912	1.196**	0.9	1.061	0.922	1.190**	0.927	1.073	0.918
	\$40,000-60,000	1.312***	0.978	1.068	0.864	1.301***	0.977	1.071	0.876	1.314***	1.028	1.098	0.874
	>\$60,000	1.346**	0.962	1.395**	0.854	1.338**	0.965	1.396**	0.865	1.394***	1.045	1.452**	0.859
% of adults with a Bachelor's degree or higher [REF: 0-20%]													
	20-40%	1.110**	1.053	0.936	0.895	1.113**	1.056	0.938	0.889	1.148***	1.101*	0.951	0.884
	40-60%	1.293***	0.836	0.905	1.093	1.302***	0.842	0.901	1.062	1.359***	0.885	0.908	1.057
	>60%	1.16	0.572**	0.932	0.447*	1.158	0.568**	0.932	0.433*	1.124	0.563**	0.915	0.430*
Homeownership Rate [REF: 0-20%]													
	20-40%	0.932	1.029	0.870*	0.932	0.927	1.033	0.870*	0.931	0.926	1.02	0.870*	0.926
	40-60%	0.839***	1.144	1.02	0.989	0.832***	1.143	1.023	0.99	0.820***	1.135	1.02	0.985
	>60%	0.899	1.269**	0.957	0.93	0.893	1.260**	0.968	0.933	0.881	1.267**	0.971	0.929
Crime Rate		1.761**	1.975***	0.258	1.031	1.808***	1.995***	0.264	1.006	1.756**	1.873**	0.229	1.014
Change in Unemployment Rate		1.106	1.904	0.449	14.727*	1.101	1.992	0.434	15.193*	0.946	1.236	0.391	13.185*
Origination year [REF: 2004]													
	2005	1.123	1.377***	1.103	1.364*	1.108	1.354**	1.112	1.365*	1.121	1.298**	1.118	1.255
	2006	0.962	1.141	0.94	1.051	0.944	1.122	0.949	1.046	0.966	1.053	0.946	0.97
	2007	1.052	1.283	0.805	0.661	1.04	1.27	0.809	0.658	1.059	1.218	0.807	0.618
	2008	1.005	0.964	0.627	0.734	1.005	0.961	0.631	0.741	0.995	1.035	0.637	0.693
Borough [REF: Manhattan]													
	Bronx	0.658***	1.23	0.998	1.028	0.644***	1.22	1	1.011	0.631***	1.197	1.008	0.933
	Brooklyn	0.691***	0.973	0.871	0.837	0.687***	0.968	0.87	0.821	0.657***	0.863	0.86	0.75
	Queens	0.588***	1.072	0.959	2.218***	0.575***	1.059	0.951	2.196***	0.536***	0.893	0.919	2.002**
Quarter of Loan Performance [REF: 2008 - 1]													
	2008 - 2	1.152**	1.695***	1.481***	1.406**	1.155**	1.701**	1.481***	1.408**	1.161**	1.630***	1.463***	1.394**
	2008 - 3	1.198**	1.575***	1.058	1.189	1.202**	1.585***	1.062	1.192	1.219**	1.441***	1.044	1.176
	2008 - 4	1.027	1.309*	0.897	0.715*	1.031	1.325**	0.903	0.716*	1.095	1.154	0.897	0.712**
	2009 - 1	0.803*	1.774***	0.723	0.656	0.807*	1.797***	0.731	0.653*	0.932	1.540***	0.731	0.658*
	2009 - 2	0.614***	1.105	1.262	0.628*	0.619***	1.128	1.284	0.627*	0.696***	0.888	1.268	0.639*
	2009 - 3	0.630***	0.946	1.435*	0.633	0.638***	0.973	1.465*	0.633	0.668***	0.725*	1.405*	0.641

2009 - 4	0.504***	1.318	0.839	0.484**	0.511***	1.362	0.856	0.484**	0.534***	0.97	0.813	0.495**
Servicer fixed effects included												
Pseudo-R2			0.1379				0.1371				0.1362	
N			258,326				258,326				258,326	

Notes:

1) The reference outcome for the odds ratio computation is "Delinquency Continues"

The grey shading and bold font indicate estimates with more important differences in statistical significance relative to the estimates from the preceding panel (i.e., either significant vs. not significant or significant at 10% level vs 1% or 5% level)

*** denotes results that are statistically significant at the 1 percent level

** denotes results that are statistically significant at the 5 percent level

* denotes results that are statistically significant at the 10 percent level

Figure 1: Outcome Categories

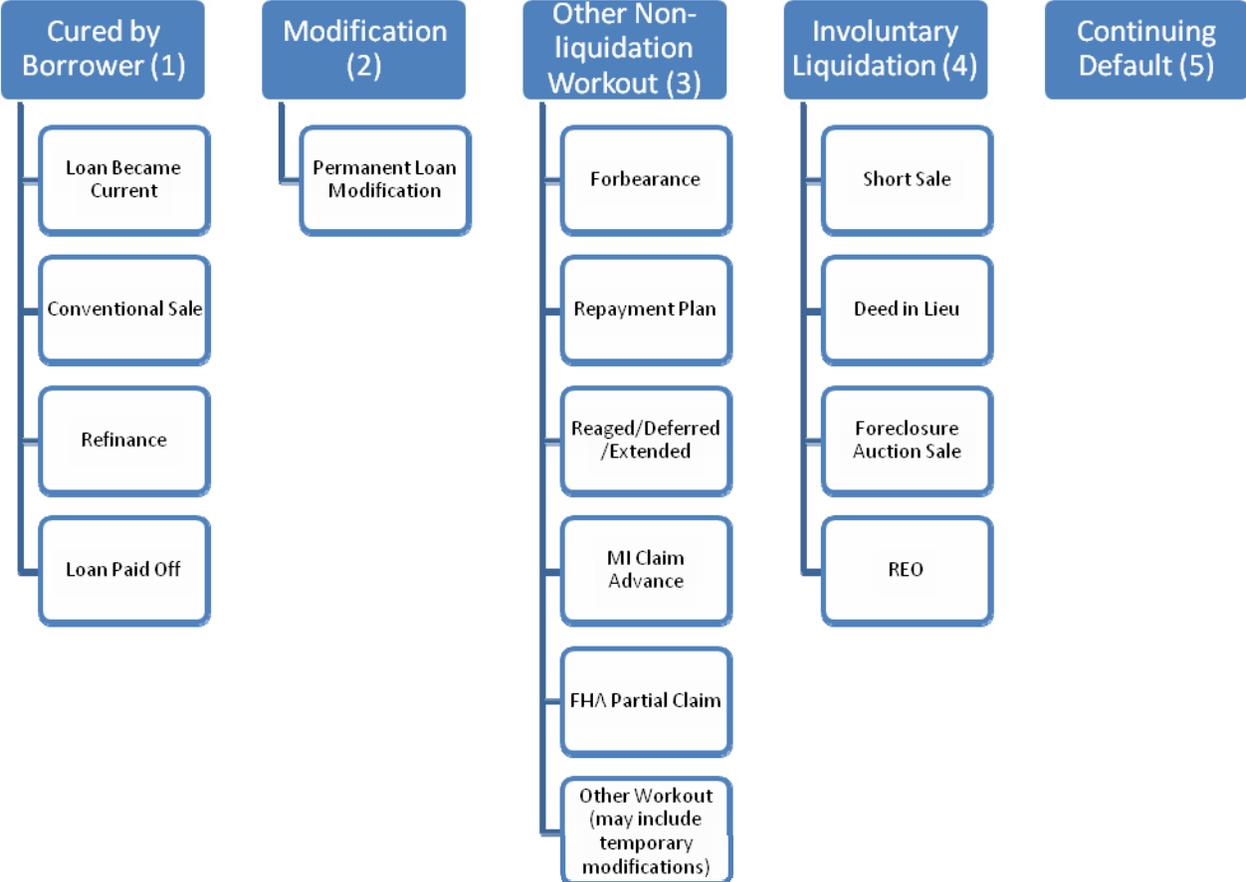


Figure 2: Map of Census Tract Boundaries, Community District Boundaries, and 2009 Foreclosure Filings in New York City

