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Performance of HAMP Versus Non-HAMP Loan Modifications – Evidence from New York City

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1. Overview

From November 2007 through March 2011, over 2.1 million mortgages were modified in the United States (U.S. Department of Treasury, 2011). Policymakers have heralded such modifications as a key to addressing the ongoing foreclosure crisis, because a successful mortgage modification can help both borrowers, by allowing them to stay current on their loans and thereby avoid foreclosure, and servicers, lenders and investors, by helping them to avoid the high costs associated with foreclosures. However, there is a lack of research about whether modifications are successful at helping borrowers stay current on their loans over the long run. If modifications are simply delaying an eventual foreclosure, then they actually may add to the cost and length of the foreclosure process.

Mortgage modifications can help a borrower to remain current on her loans by lowering the monthly payment to an affordable level. Some proponents suggest that by altering the terms of the loan, modifications may give an underwater borrower who may have been inclined to strategically default on her loan an incentive to continue paying the mortgage. Servicers can employ a variety of methods to modify mortgages. These include: (1) reducing the principal balance, (2) freezing or lowering the interest rate of the loan, and (3) extending the term of the loan, sometimes by adding missed payments to the principal. Generally (but not always) a combination of these modification strategies will result in a lower monthly payment for the borrower. However, some modifications have employed these tools in such a way that the monthly payment actually increased.

In 2009, the Obama administration introduced the Home Affordable Modification Program (HAMP), a streamlined structure for modifications that included financial incentives for servicers to modify loans. If a borrower meets strict eligibility requirements, a servicer will adjust the monthly mortgage payment to 31 percent of a borrower's total monthly income by first reducing the interest rate to as low as 2 percent, 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. Prior to HAMP, servicers could offer a range of proprietary modifications using the same tools but not following the same guidelines (and servicers can continue to do so for borrowers who do not qualify for HAMP). Little research assesses what kinds of modifications are most successful. Further, while prior research has shown that default rates vary considerably based on borrower, property, loan and servicer characteristics, little is known about whether these same characteristics predict which borrowers will default on their loans after receiving a modification.

In this paper we use a unique dataset that combines data on loan, borrower, property, and neighborhood characteristics of modified mortgages on properties in New York City to examine the determinates of successful modifications. The dataset includes both HAMP modifications and proprietary modifications. Our analysis builds upon a prior paper in which we examined the determinants of loan modifications (Been, Weselcouch, Voicu and Murff, 2011).

Our analysis advances the literature in two ways: 1) by controlling for underlying borrower, property, and neighborhood characteristics not available in other modification datasets, we can ensure that we are isolating the effects of the modification itself; and 2) by comparing HAMP and non-HAMP modifications, and controlling for the nature and magnitude of the terms of modifications, we can assess the effectiveness of the design and implementation of the HAMP program.

2. Background and Literature Review

Existing research reveals little about which modifications are successful over the longer term. OCC and OTS (2011) measured redefault rates as high as 41% based on 60+ day delinquencies 1 year after the modification, and other studies reported even higher rates,(40-50% in Adelino, Gerardi, & Willen, 2009 and 60% in Mason, 2007).[1] Existing studies focus primarily on testing whether and how the different types of modifications affect the performance of modified loans, while controlling for a limited set of other factors. Quercia, Ding, and Ratcliffe (2009) examine the relationship between redefault rates and different types of loan modifications based on a sample of nonprime loans modified in 2008 and find that modifications that reduce the principal loan amount or lower mortgage payments by at least 5% lower the risk of re-default, while modifications that increase payments do not. Haughwout, Okah, and Tracy (2009), also using data on subprime modifications that preceded HAMP, find that the re-default rate declines with the magnitude of the reduction in the monthly payment, and that the re-default rate declines relatively more when the payment reduction is achieved through principal forgiveness as opposed to lower interest rates. Finally, Agarwal *et al.* (2011), using a sample of prime and nonprime loans from an earlier release of the same database we use, find that larger payment or interest rate reductions are associated with lower redefault

[1] Adelino, Gerardi, & Willen (2009) define re-default as a loan that is 60 or more days delinquent, in the foreclosure process, or REO within 6 months of the modification. Mason (2007) defines re-default as a default within 12 to 24 months of modification.

rates, while the capitalization of missed payments and fees is associated with higher redefault rates.

The research to date is incomplete, for several reasons. First, all studies rely on older data, from the beginning of the wave of modifications that resulted from the current housing crisis, and follow the loan performance for very short spans of time following modification. Therefore, they may be of limited generalizability and do not address the effectiveness of HAMP, an issue of great policy interest in the current environment. Second, most face serious data limitations -- some infer modifications in the absence of direct data, for example, and most include a very limited set of controls and only cover nonprime loans. Last but not least, because of data limitations or methodological choices, most studies do not use hazard models, even though they are most appropriate to assess how various factors affect the probability that a borrower will stay current after a modification.

3. Empirical Model

This paper provides an empirical analysis of the factors that determine the performance of modified loans. The outcome of interest is whether a modified mortgage redefaults, where redefault is defined as being 60+ days past due. Specifically, our empirical strategy employs logit models in a hazard framework to explain how loan, borrower, property, servicer and neighborhood characteristics, along with differences in the types of modifications, affect the likelihood of redefault.

The data is organized in event history format, with each observation representing one month in which a modified loan remains current, to allow for time-varying covariates.[2] A loan drops out of the sample after it redefaults.[3] With the data structured in event history format, the logit has the same likelihood function as a discrete time proportional hazards model (Allison, 1995). In the logit framework, the probability that the loan *i* redefaults at time *t* conditional on the loan remaining current until then (i.e., the hazard of redefault) is given by:

$$\mathrm{P}_{\mathrm{it}} = \frac{e^{\beta X_{it}}}{1 + e^{\beta X_{it}}},$$

where X_{it} are the explanatory variables observed for loan *i* at time *t* (indexed by month in this paper), and β are the coefficients to be estimated. We include time since the modification process was completed among the covariates to allow the hazard to be time-dependent. To control for city-, state-, or nation-wide 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 logit coefficient estimates are used to calculate the effects of the explanatory variables on the conditional probability of redefault, in the form of odds ratios. Additionally, coefficient estimates are used to compute the effects of the explanatory variables on the cumulative probability of redefault over a specified time period since modification. These latter effects are differences (for indicator variables) and derivatives

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[2] A loan is considered current if there are no delays in payments or the payment is only 30 days past due.
[3] In principle, a loan could also drop out of the sample by being paid off. This would occur if the loan is refinanced or the house is sold, and would require a competing risk hazard model, where the competing risks would be redefault and paid-off. However, only about 100 modified loans in our data were paid off and we eliminated these loans because it was not feasible to estimate a competing risk model with so few observations for one of the outcomes.

(for continuous variables) of one minus the survivor function evaluated at the variable means for the specified time period.[4]

To gain a better understanding of the effects of various types of modifications on loan performance – an issue of heightened policy interest in the current economic environment – we estimate four regression specifications that differ by the modification features that they include. While all specifications include a HAMP indicator, the first one (M1) does not include any other modification features; the second one (M2) adds the change in monthly mortgage payment; the third one (M3) replaces the change in monthly mortgage payment with changes in individual loan terms including the change in loan balance, the change in interest rate, and a term extension indicator; and the last one (M4) includes both the change in monthly mortgage payment and the changes in individual loan terms. Thus, the first regression captures a more inclusive effect of HAMP on loan performance, but does not distinguish between effects that may be due to differences in the magnitude of payment reductions and individual term changes between HAMP and non-HAMP modifications, and effects that may be due to differences in program design. Differences in program design may include, for example, HAMP-specific features such as pay-for-performance to borrowers, a requirement that borrowers work with HUD-approved counselors to reduce their debt below 55 percent (if post-modification back-end debt-to-income (DTI) is greater than or equal to 55%), and the specific order of the waterfall.[5] While HAMP-specific eligibility criteria such as requirements that the

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[4] The cumulative probability of delinquency over a T-month period-at-risk is $1-S_i(T)$, where $S_i(T)$ is the survivor function over the T-month period. In the discrete time framework of our model, $S_i(T)= (1-P_{i1}) (1-P_{i2})\ldots(1-P_{iT})$.

[5] Another program design feature of HAMP, the requirement of a trial period prior to the borrower being granted a permanent modification, has been adopted by many servicers for their proprietary modification

borrower be an owner-occupant and that the current unpaid loan balances be within conforming loan limits also could be considered program design differences, our regressions include specific controls for such features.[6] Other distinct features of HAMP, such as the DTI eligibility criterion that qualifies only borrowers who had a front-end DTI of more than 31% at loan origination, and the requirements that this front-end DTI be reduced to 31% and that the resulting loan must pass an NPV test, tend to result in a larger reduction in monthly payment for those borrowers who receive a HAMP modification. (by comparison, proprietary modifications may be granted to borrowers with original front-end ratios below 31%, but whose payment problems are due to excessive back-end debt, and may also often result in a front-end ratio greater than 31% in order to pass NPV).

The second, third, and fourth regressions help distinguish between the program design effects and those due instead to the magnitude of payment reductions and individual term changes. The last regression also tests whether changes in individual loan terms have an impact on loan performance beyond any effects that would occur through payment changes.

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programs since the enactment of HAMP in 2009, and thus it is less likely to be responsible for any differences in redefault rates between HAMP and non-HAMP modifications in our data.

[6] Specifically, we include a dummy variable that is equal to 1 for owner-occupied properties and 0 otherwise, and the current unpaid loan balance in log terms. In preliminary work we also included additional indicators of HAMP eligibility such as property structure (1-4 family vs. multi-family) and a dummy variable equal to 1 if loan balance at modification time was below the HAMP limit; however, these variables had very low statistical significance, likely due to the lack of variation of our sample across these dimensions (e.g., 99% of the observations corresponded to 1-4 family properties and 98% of the observations had a loan balance below the HAMP limit), and thus were excluded from the final regressions. In addition, we experimented with a single indicator that captured the joint HAMP eligibility under the loan limit, owner occupancy, and property structure criteria. This indicator also had very low significance level and its inclusion left the results virtually unchanged. Results from these alternative specifications are available upon request from the authors.

In additional specifications, we explore variation in the effects over time, and test whether the effects of modification features such as payment change, balance change, rate change, and term extension vary with the borrower's credit score (FICO) and loan to value (LTV) levels. Temporal variations in any performance differential between HAMP and non-HAMP modifications may occur as a result of changes in the structure of proprietary loan modifications (perhaps in part due to the advent of HAMP itself) as well as to changes in HAMP rules (e.g., such as those in Supplemental Directive 10-01 from June 2010 including new rules regarding documentation requirements and amendments to policies and procedures related to borrower outreach and communication).

To explore these temporal dynamics, we supplement model M1 with two variables that capture the pre- and post-HAMP enactment time trends, a post-HAMP enactment dummy variable, and an interaction between the HAMP indicator and the post-HAMP enactment time trend.[7] The time trend and post-HAMP dummy variables describe the comparative loan performance of older and newer vintages of proprietary modifications, allowing for a direct comparison of the performance of the pre-HAMP and post-HAMP proprietary modifications. The HAMP indicator and its interaction with the post-HAMP trend capture temporal variations in the differential performance of HAMP modifications versus proprietary modifications granted in the post-HAMP period.

To test whether the effects of modification features vary with the FICO and LTV levels, we extend models M2 through M4 to include interactions between the relevant

[7] The post-HAMP enactment period is assumed to start in September 2009 when the first permanent HAMP modifications were completed, according to our Mortgage Metrics data extract for New York City. Thus, the post-HAMP time trend is equal to 0 if the modification was completed prior to September 2009, is equal to 1 if the modification was completed in September 2009, is equal to 2 if the modification was completed in October 2009, etc. The pre-HAMP time trend is equal to 0 if the modification was completed in August 2009 or later, is equal to -1 if the modification was completed in July 2009, is equal to -2 if the modification was completed in June 2009, etc.

modification changes and indicators for the lowest FICO category (FICO less than 560) and for the largest LTV category (LTV greater than 120 percent), respectively.

4. Data Description

To investigate the determinants of the performance of modified loans, we analyze performance between January 2008 and November 2010 for all first lien mortgages originated in New York City from 2004 to 2008 and still active as of January 1, 2008 in the OCC Mortgage Metrics database. OCC Mortgage Metrics provides loan-level data on loan characteristics and performance, including detailed information about loan modifications, for residential mortgages serviced by selected national banks and federal savings associations. The database includes loans serviced by 9 large mortgage servicers covering 63 percent of all mortgages outstanding in the United States, and includes all types of mortgages serviced, including both prime and subprime mortgages (OCC and OTS, 2011).[8] 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).

[8] 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 2011, the servicers in the OCC Mortgage Metrics include 8 national banks and one thrift with the largest mortgage-servicing portfolios among national banks and thrifts (OCC and OTS, 2011).

An observation in the data set is a loan in a given month. Although we look at all loans originated between 2004 and 2008, monthly performance history for those loans is only available from January 2008 through November 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.[9] 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.

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.[10] Second, we merge information on whether the borrower received foreclosure prevention counseling or other assistance from any of the non-profit organizations coordinated by the Center for New York City Neighborhoods (CNYCN).[11]

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[9] 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 percent of residential property sales in the four boroughs studied were coops. Further, our match rate was lowest (44 percent) in Manhattan where 48 percent 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 percent).

[10] 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).

[11] 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

Third, 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.[12] Fourth, we link information on the demographic characteristics of census tracts using the 2000 Census. Finally, we add the rate of mortgage foreclosure notices (*lis pendens*) at the census tract level.[13]

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 variables – specifically, the unemployment rate and the rate of house price appreciation – census tract data was not available, so we had to use community district level data.[14] To illustrate the relative size of each jurisdiction, Figure 1 shows census tract boundaries, community district boundaries and *lis pendens* filed in the four boroughs of New York City in 2009.[15]

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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. One of the co-authors, Vicki Been, serves on the Board of Directors for CNYCN.

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

[13] The *lis pendens* are from Furman Center's calculations based on data 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.

[14] Community districts are political units unique to New York City. Each of the 59 community districts has a Community Board that makes non-binding recommendations about applications for zoning changes and other land use proposals, and recommends budget priorities.

[15] 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.

4.1 Descriptive Statistics

Table 1 presents descriptive statistics for the dataset used in the estimation, organized in six panels: A – delinquency rates; B – modification features; C – loan characteristics; D – borrower and property characteristics; E – neighborhood characteristics; and F – servicer characteristics. Panel A shows that nearly 30 percent of the modified loans in our data became seriously delinquent following modification. A more informative description of the performance of modified loans is provided by the Kaplan-Meyer survival graph in Figure 2A. The survival graph plots, over time since modification, the fraction of the modified loans that have "survived", in that they have not yet redefaulted. Given our definition of redefault as the payment becoming 60 days past due, the first month that a loan is "at risk" is in the second month after modification, and the origin of the survival plot in Figure 2A corresponds to the first month following modification. Notice that, starting in the second month after modification, there is a steady transition of loans into serious delinquency with the pace diminishing beyond the 15th month following modification. The survival rate one year after modification is just below 60 percent. Figure 2B shows sharp differences in survival rates between the loans that received HAMP modifications and those that received proprietary modifications. For example, the survival rate of HAMP loans one year after modification is over 30 percentage points higher than the survival rate of non-HAMP loans.

Panel B of Table 1 presents descriptive statistics for the types of the modifications in our sample. One third of the loans received HAMP modifications. The modification process resulted in payment reductions for most – but not all - loans. While over 80 percent of the modifications resulted in payment reductions, almost 7 percent resulted in payment increases and nearly 4 percent produced no payment change. On average, the mortgage payment was reduced by 28 percent. A majority of the modifications resulted in higher balances, while only about 10 percent resulted in lower balances and almost 15 percent produced no balance change. On average, the balance was increased by 2.6 percent. The prevalence of balance increases is not surprising given that capitalization – the addition of arrearages to the loan balance – is a frequent component of the modifications in our data, whereas principal write-down is very rarely used.[16] Over 75 percent of the modifications resulted in a decrease in interest rates, and the rate reductions were substantial -- 2.8 percentage points, on average. Approximately 45 percent of the modifications included term extensions, however the actual size of the term change was largely missing in our data and thus we could not use this information in our analysis. Overall, these patterns suggest that servicers aim to make the loans more affordable while minimizing losses in the underlying principal.

Panel C presents descriptive statistics for the characteristics of the loans in our dataset. Our dataset covers a range of loan products. Of the 6,541 modified loans in our dataset: there is a nearly even split between prime and non-prime loans;[17] 57 percent have fixed interest rates while the remainder have adjustable rate mortgages; 14 percent were interest only at origination and 79 percent are conventional mortgages. Our sample also includes a mix of loans that were privately securitized, bought by the GSEs and held in portfolio. This robust mix of loan products, uses and investors allows us to give a more

[16] Almost 90 percent of the modifications involved capitalization whereas only about 2 percent included principal write-down.
[17] Loans are categorized as prime or non-prime based on the credit grades defined by the servicers.

complete analysis than the existing literature because our conclusions are not limited to only one loan type or group of loans.

The relative interest rate after modification for FRMs is calculated as the interest rate minus the Freddie Mac average interest rate for prime 30-year fixed rate mortgages during the first month after the modification was completed. For ARMs, it is the interest rate minus the six-month London Interbank Offered Rate (LIBOR) during the first month after the modification. In our sample, nearly 30 percent of the fixed rate loans have relative interest rates between 1 and 2 percentage points over the market index and over 50 percent of the adjustable rate loans have relative interest rates larger than 4 percentage points at origination.

The performance of the modified loans was poor prior the modification. The average loan was seriously delinquent in 37 to 45 percent (depending on origination year) of the months from the pre-modification period covered by Mortgage Metrics (i.e., starting from the beginning of 2008). Additionally, 17 percent of the loans had a *lis pendens* (notice of foreclosure) filed before being modified.

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 42,380 loan-months. The last five descriptive statistics in Panel B are measured across all loan-months in our sample. Only a small proportion of the loan-months for ARMs (14%) involved a rate that had been reset before the month being studied.[18] The average LTV for all of the loan-months in our sample was 107.7 percent.[19]

[18] Those rate resets do not include those due to a modification.

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

As Panel D shows, over 90 percent of the borrowers in our sample report that they are owner-occupiers. We constructed borrower-months for those borrower level variables that change over time. The current FICO score[20] has a mean of 597 across all borrower-months, and over 60 percent of borrower-months have FICO scores of 620 or less. On average, FICO scores of the borrowers in our sample declined by 88 points from origination to the month in which the loan was modified. Only 3.5 percent of the borrowers received foreclosure counseling at some point prior to being granted the loan modification.

Some of the characteristics of the neighborhoods in which the properties in our sample are located (shown in Panel E) are different from the neighborhood characteristics of the four boroughs of New York City included in our analysis. Specifically, the 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 \$40,000 or more than \$60,000.

Panel E also reveals some interesting neighborhood shifts from the time of modification to the loan month studied. In particular, in the neighborhoods where the loans in our sample are located, house prices decreased, on average, by 6 percent between the month the modification process was completed and the loan month being studied.

[20] The current FICO score is based on periodically updated information provided by the servicers. The score is typically updated quarterly however the frequency of updates may vary across servicers and even for the same servicer.

Our model also includes servicer fixed effects. Panel F shows the range of FICO scores and LTV ratios at the time of loan origination for the modified loans in our sample across the 9 servicers that serviced them. Average FICO scores range from 644 to 695. LTVs range from .731 to .794.

One of the goals of our study is to evaluate the impact of HAMP, among other modification features, on the post-modification loan performance. To alleviate concerns that any estimated differences in redefault rates between loans modified through HAMP and loans that received non-HAMP modifications may be due to unobserved differences in the quality of loans that received different types of modifications, our models include a comprehensive list of borrower, loan, and neighborhood characteristics, as detailed above. Additionally, we also note that the vast majority of the loans in our sample satisfy the basic HAMP eligibility criteria with respect to loan limit, owner-occupancy, and property structure.[21] Nonetheless, it is reassuring to note that differences in many observed characteristics between the HAMP and non-HAMP loan samples do not indicate that one set of loans is clearly "better" than the other. As shown in Table 2, while HAMP is associated with significantly more advantageous changes in loan terms,[22] the loan, borrower, and neighborhood characteristics of the two loan samples are, in general, fairly similar. For example, the average FICO score and LTV, both at the time of origination and at the time of modification, are very similar. The two pools of loans also appear to have had similar performance prior to modification, as measured by the

[21] See footnote 6 above for specific statistics.
[22] The significantly larger payment reduction for HAMP is not surprising given the DTI-related requirements of HAMP described above.

percentage of months the loans were seriously delinquent before modification[23] and by whether there were any *lis pendens* filed before modification. Loan products differ somewhat along several dimensions, however these differences do not consistently suggest that one set of loans would be expected to perform better over time. For example, 56 percent of the non-HAMP loans are subprime whereas only 45 percent of the HAMP loans are subprime but, on the other hand, the share of FRMs is larger in the non-HAMP sample (60 percent) than in the HAMP sample (50 percent). Similarly, the relative interest rate at origination for FRMs is lower whereas that for ARMs is higher in the HAMP set. Moreover, and more importantly perhaps, the proportions of loans with very risky characteristics such as interest only and low or no documentation are very similar in the two samples. Finally, comparing the neighborhood characteristics for the two sets of loans, the only differences occur in terms of unemployment rate at modification and house price appreciation between origination and modification, with the HAMP loans faring somewhat worse along both dimensions.[24]

5. Results

Table 3 presents, in the first four columns, odds ratio estimates -- i.e., the impacts explanatory variables have on the conditional odds of redefault at a given point in time (conditional on the loan being current until that time) -- for the four logit regressions described in Section 3. The table also shows, in the last four columns, estimates of the impact of selected explanatory variables – those with statistically significant effects on

[23] This measure was very similar between the two samples for the loans originated

[24] However, neighborhood differences, in general, should be of little concern with respect to endogeneity biases in the HAMP effect estimate given that neighborhood conditions turn out to have little influence on post-modification loan performance, as shown below.

the conditional odds of redefault – on the predicted probability that the average modified loan becomes seriously delinquent over the 12 months following the modification. Below, we review in detail the results for these regressions.

5.1 Effects of Variables on the Conditional Odds of Redefault

Modification Features. The first set of rows in Table 3 show the impacts modification features have on loan performance. These effects are, in general, highly statistically significant and economically important. In all specifications, HAMP is associated with sizable reductions in the odds of redefault. The overall HAMP effect from the first regression is a 48 percent reduction in the odds of redefault. Controlling for changes in mortgage terms dampens that effect somewhat. This is not surprising given that HAMP is associated with more advantageous changes in loan terms (as shown in Table 2). Nonetheless, the improvement in loan performance remains significant (a 27 to 33 percent reduction in the redefault odds, depending on the specification), even after controlling for these changes. Thus, the program design may play a significant role in how the loan fares after modification.

Modifications that result in larger payment reductions make the loan less likely to redefault; a 1 percentage point increase in the payment reduction is associated with a 1.6 percent decline in the odds of redefault, as shown in model M2. Looking at the effects of the individual term changes in model M3, a larger balance decrease (or a smaller balance increase) makes redefault less likely; if the balance reduction grows by 1 percentage point, the odds of redefault decrease by 1.8 percent. The larger the interest rate reduction, the smaller the odds of redefault; a 1 percentage point increase in the rate reduction is associated with a10 percent decline in the redefault odds. If the modification includes a term extension, the odds of redefault are 18 percent lower than if a term extension is not granted. Interestingly, some of the effects of interest rate and balance reductions still remain, while the effect of a term extension disappears after controlling for the size of the payment reduction (see model M4). While the persistence of the balance change effect is not very surprising given that this modification also reduces the principal burden (in addition to reducing the monthly payment), the reason for the persisting effect of a rate change is less clear and deserves further investigation.

Loan characteristics. Loans that the servicer defines as non-prime at origination were more likely to redefault than prime loans. Conventional mortgages with private mortgage insurance (PMI) were less likely to redefault than government and conventional mortgages without PMI, however the differences diminish or disappear after controlling for the payment reduction from modification. While in previous research (Been, Weselcouch, Voicu, and Murff, 2011) we found that securitized loans guaranteed by the GSEs were more likely than all other loans to be modified, we find here that the modified GSE loans are more likely to redefault than all other loans.

We next focus on the pricing of loans after modification. Both for FRMs and ARMs, loans with interest rates after modification that are much higher than the market index (more than 3 points higher for FRMs and more than 4 points higher for ARMs) are significantly more likely to become seriously delinquent after 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 effects could be picking up some borrower risk that is not reflected in the specific risk controls we include in our model.

We find that the loan performance post modification is affected by the performance prior to modification as measured by the percent of the months from the pre-modification period that the loan was seriously delinquent. Specifically, if that measure of pre-modification performance increases by 1 percentage point, the odds of redefault after modification increase by 0.7 to 1.8 percent, depending on year of origination and regression specification.

The post modification loan performance does not differ significantly by current LTV levels, however, the higher the dollar value of the current outstanding balance, the higher the likelihood of redefault. A 1 percent increase in loan balance is associated with a 1.2 percent increase in the odds of redefault. This effect suggests that the loan limit associated with HAMP is a desirable feature.

The impact of time elapsed since modification is associated with an increased likelihood of delinquency. The impact of time elapsed since modification can be thought of as baseline odds. All other variables are interpreted as proportional shifts up or down from the baseline odds.

Finally, we find differences in the performance of loans modified by different servicers, however we do not have enough servicer-specific information to further explore the reasons for these differences. Thus, future research incorporating detailed servicer characteristics may be warranted to better understand these differences."

Borrower characteristics. FICO score is the only borrower characteristic that matters for loan performance. Specifically, borrowers with higher current FICO scores were less likely to redefault, and the differences in loan performance across the various credit score brackets are large. For example, a borrower in the highest bracket

(FICO>=720) has almost 85 percent lower odds of redefaulting, and one in the middle bracket (650<=FICO<680) has almost 60 percent lower odds of redefaulting relative to a borrower in the lowest bracket (FICO<560). The lack of a significant effect on the owner-occupancy variable suggests that the HAMP's exclusive focus on owner-occupants may not be warranted from an efficiency perspective. The insignificance of the foreclosure counseling variable suggests that counseling is resulting in modifications that are no more or less successful than average, even though prior work shows that counseling increases the likelihood that a borrower will receive a modification (Been, Weselcouch, Voicu and Murff, 2011).

Neighborhood characteristics. Table 3 also explores whether socio-economic characteristics of the neighborhood affect the post-modification loan performance. Interestingly, we find little evidence of any neighborhood effects. The lack of any significant effect of house price depreciation or lis pendens rate is puzzling, because Chan et al. (2011) shows that those factors are important for default, and one would reason that they would be similarly likely to affect redefault. Our result might be an indicator that once a family has received a modification, they are not being influenced by the neighborhood property values because the payment reduction is good enough to allow them to live in the house at the equivalent of market rents (so it does not matter if the house value falls).

5.2 Effects of Variables on the Probability of Redefault over 12 Months since Modification

Modification Features. HAMP has a strong effect on the predicted 12-month probability of redefault. The overall effect is a 14 percentage-point reduction in that probability, whereas the residual effect after controlling for changes in mortgage terms varies between 6.8 and 8.6 percentage points. The other modification features in our models have, with one exception, relatively small, albeit statistically significant, impacts. A 10 percentage-point increase in the mortgage payment reduction reduces the predicted probability of redefault over the first year post modification by 0.3 - 0.4 percentage points. If the balance reduction grows by 10 percentage points, the predicted redefault probability decreases by 0.3 - 0.5 percentage points, whereas a 1 percentage point increase in the rate reduction is associated with a 0.13 – 0.27 percentage point decline in that probability (with the smaller effects occurring in the regression that controls for payment changes). The one exception is the relatively large impact of a term extension -- if the modification includes a term extension, the probability of redefault is 4.4 percentage points lower than in the absence of that feature. However, this effect disappears when we control for the monthly mortgage payment change.

Loan Characteristics. The 12-month probability of redefault for non-prime loans is 3.4 to 3.9 percentage points higher than that for prime loans. Probability of redefault for GSE loans is 4.6 to 4.9 percentage points higher than that for loans held by private investors. Loans with interest rates after modification that are much higher than the market index have a probability of redefault which is 10 to 14 percent higher than that for loans with below market rates.

If the percentage of the months that the loan was seriously delinquent in the pre-modification period increases by 10 percentage points, the redefault probability over the first year post modification increases by 0.2 to 0.5 percentage points. A 1 percent increase in the outstanding loan balance is associated with a 0.5 percentage point increase in the likelihood of redefault.

Borrower characteristics. The current FICO score has a strong effect on the cumulative probability of redefault. For example, the 12-month redefault probability for a borrower with FICO greater than 720 is about 34 percent higher than that of a borrower with FICO less than 560.

Figure 3 graphs the effects of the dummy variables described above on the predicted survival probability as a function of time since modification. The graphs are based on the estimates from the regression model M2. Since survival probability over a given time period is 1 – probability of delinquency over that period, the graphed effects are the negative of the effects on the cumulative probability of redefault. Notice that the magnitudes of all effects increase with the time since modification.

5.3 Do HAMP Effects Vary over Time?

The results in Table 4 offer insights about the temporal dynamics of the comparative performance of HAMP and non-HAMP modifications. Notice first that the odds ratios for the pre- and post-HAMP time trend variables are statistically significant, smaller than 1, and very similar in magnitude[25], whereas the odds ratio for the post-HAMP indicator is not statistically significant. These results indicate that newer proprietary modifications are associated with lower conditional odds of redefault, and this improvement appears unrelated to the advent of HAMP. Second, we find that HAMP

[25] In addition, the difference in odds ratios is not statistically significant.

modifications result in significantly lower odds of redefault relative to the proprietary modifications from the post-HAMP period.[26] The newer HAMP modifications result in performance improvements relative to older ones similar to those in the non-HAMP sector, which leaves the HAMP vs non-HAMP differential relatively constant over time.[27]

5.4 Do Effects of Modification Features Vary with FICO and LTV?

In alternative specifications, shown in Table 5, we took steps to test whether the effects of modification features such as payment change, balance change, rate change, and term extension vary with the FICO and LTV levels. We find that the balance change effects discussed in the previous section only occur for the borrowers with negative equity. This suggests that principal write-downs may be more effective in preventing redefault if targeted to underwater borrowers. We also find that a reduction in interest rate may be less effective in improving loan performance for the borrowers with the lowest credit scores than for the more creditworthy borrowers, controlling for changes in monthly payment. Finally, we find no evidence that the effects of payment changes and term extensions on the loan's post modification performance vary with FICO and LTV.

6. Conclusion

Our results demonstrate that borrowers who receive HAMP modifications have been considerably more successful in staying current than those receiving non-HAMP

[26] Almost 60 percent lower as indicated by the odds ratio for the HAMP indicator.
[27] As indicated by the statistically insignificant odds ratio for the Post-HAMP Time Trend X HAMP interaction term.

modifications. HAMP modifications have resulted, on average, in modifications that are on terms substantially more favorable to the borrower than other modifications, and not surprisingly, when mortgages are made more affordable to the borrower, the borrower performs better. But our results also show that successful modifications are not simply a matter of bringing the cost of the mortgage down to an affordable level. Overall, getting a HAMP modification improves the conditional odds that the borrower will not redefault by about 48 percent, but more than half of that effect remains after controlling for the terms of the modification, which suggests that the design or implementation of the HAMP program themselves are promoting successful modifications. Modification programs offered outside of the HAMP program accordingly would be well advised to adopt HAMP features. While this research is unable to isolate precisely which features are reducing the likelihood of redefault, non-HAMP programs may wish to experiment with adopting various features such as the waterfall protocol. However, caution should be applied in adopting the stricter eligibility requirements of HAMP, as these may significantly reduce the number of troubled borrowers who would qualify for a modification.

Both HAMP and non-HAMP modifications may need to recalibrate their assessments of when modifications are likely to result in a higher return than foreclosure or denial of the modification, given the findings that relatively small changes in modification terms can have a significant effect on the probability of redefault. A 1 percentage point increase in the payment reduction is associated with a 1.6 percent decline in the conditional odds of redefault, for example, and a 1 percentage point decrease in interest rates decreases the conditional odds of redefault by 10 percent.

Although few modifications are resulting in principle reductions, increasing the balance reduction by 1 percentage point reduces the conditional odds of redefault by 1.8 percent. However, in modification decisions, this benefit of a balance reduction should be weighed against the negative impact the reduction would have on the net present value of the modified loan, to evaluate the resulting net return to the investor.

Our analysis of the temporal dynamics of the performance of HAMP and non-HAMP modifications reveals some encouraging trends. While the performance differential between the HAMP and non-HAMP modifications seems relatively steady across modification vintages, the more recent vintages – both in the HAMP and the non-HAMP sector – are associated with improved loan performance relative to the earlier ones.

Our results also suggest the borrowers with whom servicers and counselors should be especially careful to review the costs and benefits of a modification over the long run: low credit score borrowers with high balance subprime loans, guaranteed by the GSEs, originated at rates substantially higher than market, and with many months of delinquency have particular difficulties carrying even modified loans. Our results also suggest that for borrowers with the lowest credit scores, interest rate reductions may be less effective than for other borrowers. Interestingly, the determinants of which borrowers are getting modifications (based on the prior research in Been, Weselcouch, Voicu and Murff, 2011) – subprime, high LTV, ARM, low FICO borrowers in less rapidly depreciating neighborhoods – do not turn out to be the determinants of which modifications succeed. They may be the servicer's attempt to prevent strategic default, or may reflect the servicer's belief that those homes will command so little on the market that they are not worth foreclosing on. Including the factors that predict the success of modified loans in the decisioning process that determines who gets modifications may help increase the efficiency of loan default resolutions.

While many observers are seriously disappointed with the failure of the HAMP program to modify more of the millions of mortgages in default, our results reveal that those modifications that have been made under the HAMP program have performed well, relative to other modifications.

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Table 1. Descriptive Statistics

A. Outcomes of Modified Loans

Outcome	% of all loans
Remains Current	70.7
Becomes 60+Days Delinquent	29.3

B. Modification Features

Variable		Mean	% of Loans with:[1] Reduction	Increase	No Change
HAMP		0.330			
Monthly Mortgage Payment Change (pre ─ post mod, as % of pre mod)		28.215	81.3	6.7	3.8
	(missing payment change indicator)	0.083			
Principal Balance Change (pre ─ post mod, as % of pre mod)		-2.623	9.6	71.8	14.8
	(missing balance change indicator)	0.038			
Interest Rate Change (pre ─ post mod, in percentage points)		2.807	75.1	2.8	11.2
	(missing rate change indicator)	0.109			
Term Extension (Yes=1; No=0)		0.449			
	(missing term extension indicator)	0.026			
Number of Loans		6,541			

C. Loan Characteristics

Variable		Mean
Credit Class		
	Prime	0.449
	Non-Prime	0.526
	(missing credit class indicator)	0.025
Product Description		
	FRM	0.568
	ARM 2/28	0.020
	ARM 3/27	0.015
	ARM (other)	0.261
	Other	0.135
Interest Only at Origination		0.142
	(missing interest only indicator)	0.009
Full Documentation		0.409
	(missing full documentation indicator)	0.001
Product Group		
	Government (FHA, VA)	0.079
	Conventional with PMI	0.115
	Conventional	0.789
	Other	0.017
Relative Interest Rate after Modification (FRMs):[3]		
	<0	0.210
	0-1	0.157
	1-2	0.295
	2-3	0.197
	>3	0.111
	(missing interest rate indicator)	0.030

Relative Interest Rate after Modification (ARMs):[2]		
	<0	0.345
	0-2	0.036
	2-4	0.077
	>4	0.517
	(missing interest rate indicator)	0.024
Investor Type		
	Private Investor	0.364
	GSE	0.433
	Held in Portfolio	0.173
	(missing investor type indicator)	0.030
% Months the Loan was 60+ DPD before Modification X Origination Year[5]		
	X 2004	45.352
	X 2005	39.107
	X 2006	39.929
	X 2007	39.956
	X 2008	36.912
Lis Pendens Filed before Modification		0.171
Number of Months Post-Adjustment (ARMs):[2]		
	before 1st adjust or no adjust	0.863
	0-3	0.016
	4-6	0.015
	>6	0.106
Current LTV[4]	Mean	1.077
	<80%	0.173
	80-100%	0.229
	100-120%	0.270
	>120%	0.319
	(missing LTV indicator)	0.010
log (Current Unpaid Balance)		12.855
Loan Age (months)		44.227
Time since Modification (months)		6.685
Number of Loans		6,541
Number of Loan-Months		42,380

D. Borrower and Property Characteristics

Variable		Mean
Owner Occupier		0.913
Borrower Race/Ethnicity		
	Non-Hispanic Black	0.281
	Non-Hispanic Asian	0.085
	Non-Hispanic Other	0.012
	Non-Hispanic White	0.152
	Hispanic	0.147
	(missing race/ethnicity indicator)	0.323
Received Foreclosure Counseling before Modification		0.035
FICO Score Decline between Origination and Modification[4]		87.760
	(missing FICO score decline indicator)	0.067

Current FICO Score[4]	Mean	597.009
	<560	0.364
	560-620	0.248
	620-650	0.112
	650-680	0.082
	680-720	0.085
	>=720	0.087
	(missing FICO score indicator)	0.022
Number of Loans		6,541
Number of Loan-Months		42,380

E. Neighborhood Characteristics

		Estimation Sample	NYC (4 boroughs)
Variable		Mean	Mean
Neighborhood Racial Composition			
% Non-Hispanic Black			
	<20%	0.377	0.584
	20-40%	0.092	0.117
	40-60%	0.083	0.085
	60-80%	0.143	0.089
	>80%	0.305	0.125
% Hispanic			
	<20%	0.631	0.551
	20-40%	0.201	0.203
	>40%	0.168	0.246
% Non-Hispanic Asian			
	<20%	0.884	0.840
	20-40%	0.102	0.124
	>40%	0.014	0.036
Other Neighborhood Characteristics			
% Foreign Born			
	<20%	0.132	0.181
	20-40%	0.459	0.414
	40-60%	0.339	0.307
	>60%	0.069	0.098
Median Household Income (1999)			
	<$20,000	0.049	0.121
	$20,000-40,000	0.360	0.435
	$40,000-60,000	0.495	0.312
	>$60,000	0.096	0.132
Origination Year			
	2004	0.077	
	2005	0.173	
	2006	0.324	
	2007	0.308	
	2008	0.118	
Borough			
	Manhattan	0.018	
	Bronx	0.153	

	Brooklyn	0.287
	Queens	0.542
Quarter of Loan Performance		
	2008 - 1	0.001
	2008 - 2	0.009
	2008 - 3	0.011
	2008 - 4	0.018
	2009 - 1	0.024
	2009 - 2	0.043
	2009 - 3	0.065
	2009 - 4	0.080
	2010 - 1	0.102
	2010 - 2	0.171
	2010 - 3	0.262
	2010 - 4	0.214
Unemployment Rate (%)		10.079
Recent Foreclosure Rate		
	<1%	0.266
	1-2%	0.315
	2-3%	0.242
	>3%	0.177
HP Appreciation (%)		-5.854
Number of Loans		6,541
Number of Loan-Months		42,380

F. Servicer Characteristics: Mean FICO and LTV at Origination[4]

Servicer	FICO	LTV
1	643.7	0.794
2	651.4	0.775
3	662.4	0.753
4	695.2	0.774
5	667.4	0.782
6	649.8	0.731
7	685.2	0.754
8	675.3	0.770
9	652.1	0.770

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 percentages in the rows of this panel do not add up to 100 due to the exclusion of missing values; the share of loans with missing values for the given feature is indicated by the mean of the corresponding missing value indicator in the Mean column.

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) The mean is computed using only the loans originated in the relevant year.

Table 2. Characteristics of HAMP and Non-HAMP Loans

Variable		HAMP Mean	Non-HAMP Mean
Modification Features			
Monthly Mortgage Payment Change (pre — post mod, as % of pre mod)		42.587	20.177
Principal Balance Change (pre — post mod, as % of pre mod)		0.520	-4.262
Interest Rate Change (pre — post mod, in percentage points)		4.171	2.023
Term Extension (Yes=1; No=0)		0.558	0.395
Loan Characteristics			
Credit Class[1]			
	Prime	0.543	0.402
	Non-Prime	0.446	0.558
Product Description			
	FRM	0.500	0.604
	ARM 2/28	0.004	0.028
	ARM 3/27	0.003	0.023
	ARM (other)	0.318	0.229
	Other	0.174	0.116
Interest Only at Origination		0.119	0.133
Full Documentation		0.435	0.392
Relative Interest Rate at Origination (%) (FRMs):[2]		-0.022	0.159
Relative Interest Rate at Origination (%) (ARMs):[3]		1.738	1.558
% months the loan was 60+ DPD before modification X origination year[4]			
	X 2004	39.669	46.790
	X 2005	44.695	37.495
	X 2006	42.375	38.915
	X 2007	40.159	39.803
	X 2008	35.168	38.124
Lis Pendens Filed before Modification		0.160	0.176
LTV at Origination		0.766	0.769
LTV at Modification		1.075	1.029
Borrower Characteristics			
FICO Score at Origination		678.598	657.938
FICO Score at Modification		576.217	577.481
Neighborhood Characteristics			
Median Household Income (1999)			
	<$20,000	0.035	0.057
	$20,000-40,000	0.341	0.369
	$40,000-60,000	0.524	0.481

	>$60,000	0.100	0.093
Borough			
	Manhattan	0.005	0.025
	Bronx	0.137	0.160
	Brooklyn	0.260	0.300
	Queens	0.598	0.514
Unemployment Rate at Modification (%)		10.574	9.239
Recent Foreclosure Rate before Modification (%)		1.917	1.906
HP Appreciation between Origination and Modification (%)		-28.645	-19.965
Number of Loans		2156	4385

Notes

Means are computed using only non-missing values.

1) Shares do not add up to 1 because of the exclusion of share of loans with missing credit class.

2) The means are computed using only the FRMs.

3) The means are computed using only the ARMs.

4) The mean is computed using only the loans originated in the relevant year.

Table 3. Baseline Models

Variable		Effects on hazard of re-default (odds ratios) M1	M2	M3	M4	Effects on probability of re-default over 12 months since modification (%) (selected variables) M1	M2	M3	M4
Modification Features									
HAMP		0.523***	0.664***	0.690***	0.728***	-13.57 ***	-8.64 ***	-7.97 ***	-6.77 ***
Monthly Mortgage Payment Change (pre— post mod, as % of pre mod)			0.984***		0.988***		-0.04 ***		-0.03 ***
	(missing payment change indicator)		1.103		1.030				
Principal Balance Change (pre— post mod, as % of pre mod)				0.982***	0.987**			-0.05 ***	-0.03 **
	(missing balance change indicator)			1.254*	1.218				
Interest Rate Change (pre— post mod, in percentage points)				0.901***	0.950***			-0.27 ***	-0.13 ***
	(missing rate change indicator)			0.829**	0.896				
Term Extension (Yes=1, No=0)				0.822***	0.909			-4.41 ***	-2.13
	(missing term extension indicator)			1.030	1.048				
Loan Characteristics									
Credit Class Non-Prime		1.177**	1.193**	1.164**	1.180**	3.67 **	3.85 **	3.36 **	3.60 **
	(missing credit class indicator)	3.036***	3.140***	3.043***	3.095***				
Product Description [REF: FRM]									
	ARM 2/28	0.988	1.038	1.040	1.052				
	ARM 3/27	0.819	0.843	0.864	0.860				
	ARM (other)	0.766*	0.862	0.859	0.891				
	Other	0.876	0.908	0.924	0.924				
Interest Only at Origination		0.911	0.950	0.946	0.969				
	(missing interest only indicator)	0.708	0.702	0.588*	0.644				
Full Documentation		1.096	1.092	1.092	1.090				
	(missing full documentation indicator)	1.916	1.840	1.853	1.806				
Product Group [REF: Conventional]									
	Government (FHA, VA)	1.132	1.094	1.132	1.105				
	Conventional with PMI	0.798**	0.856*	0.830**	0.861	-4.91 **		-4.01 **	
	Other	1.121	1.107	1.133	1.118				
Relative Interest Rate after Modification (FRMs) [REF: <0]									
	0-1	1.370***	1.122	1.196	1.104	7.18 ***			
	1-2	1.398***	1.143	1.206	1.111	7.71 ***			
	2-3	1.379***	1.149	1.225*	1.124	7.35 ***			
	>3	1.635***	1.562***	1.542***	1.524***	11.88 ***	10.84 ***	10.41 ***	10.16 ***
	(missing interest rate indicator)	0.781*	0.795*	0.826	0.820				

Relative Interest Rate after Modification (ARMs) [REF: <0]									
	0-2	0.797	0.736	0.723	0.716				
	2-4	1.478**	1.228	1.306	1.207	8.55 **			
	>4	1.811***	1.569***	1.582***	1.512***	13.91 ***	10.54 ***	10.70 ***	9.63 ***
	(missing interest rate indicator)	0.744	0.810	0.765	0.812				
Number of Months Post-Adjustment (ARMs) [REF: <0]									
	0-3	0.883	0.861	0.891	0.867				
	4-6	1.149	1.126	1.150	1.119				
	>6	0.879	0.877	0.887	0.870				
Investor Type [REF: Private Investor]									
	GSE	1.217**	1.230***	1.239**	1.229**	4.58 **	4.72 ***	4.90 **	4.67 **
	Held in Portfolio	1.113	1.074	1.155	1.100				
	(missing investor type indicator)	1.031	1.051	1.004	1.034				
% Months the Loan was 60+ DPD before Modification X Origination Year									
	X 2004	1.011***	1.011***	1.011***	1.011***	0.03 ***	0.03 ***	0.03 ***	0.03 ***
	X 2005	1.011***	1.010***	1.010***	1.010***	0.03 ***	0.03 ***	0.03 ***	0.02 ***
	X 2006	1.008***	1.008***	1.008***	1.007***	0.02 ***	0.02 ***	0.02 ***	0.02 ***
	X 2007	1.011***	1.011***	1.010***	1.011***	0.03 ***	0.03 ***	0.03 ***	0.03 ***
	X 2008	1.018***	1.017***	1.018***	1.017***	0.05 ***	0.04 ***	0.05 ***	0.04 ***
Lis Pendens Filed before Modification		1.057	1.039	1.053	1.034				
Current LTV [REF: <80%]									
	80-100%	1.053	1.045	1.040	1.041				
	100-120%	1.035	1.022	0.992	1.002				
	>120%	1.114	1.108	1.056	1.071				
	(missing LTV indicator)	4.678***	4.507***	4.507***	4.442***				
log (Current Unpaid Balance)		1.213**	1.223**	1.213**	1.214**	0.54 **	0.51 **	0.51 **	0.49 **
Loan Age		0.994	0.991	0.990	0.990				
Time since Modification		1.053***	1.038***	1.046***	1.039***				
Borrower and Property Characteristics									
Owner Occupier		0.910	0.913	0.905	0.909				
Current FICO Score [REF: <560]									
	560-620	0.620***	0.613***	0.620***	0.616***	-13.49 ***	-13.57 ***	-13.35 ***	-13.40 ***
	620-650	0.429***	0.423***	0.429***	0.425***	-21.59 ***	-21.51 ***	-21.31 ***	-21.30 ***
	650-680	0.421***	0.408***	0.420***	0.411***	-21.94 ***	-22.20 ***	-21.74 ***	-21.91 ***
	680-720	0.212***	0.204***	0.212***	0.207***	-32.06 ***	-31.87 ***	-31.60 ***	-31.53 ***
	>=720	0.172***	0.164***	0.166***	0.165***	-34.15 ***	-33.94 ***	-33.99 ***	-33.63 ***
	(missing FICO score)	0.555***	0.566***	0.553***	0.562***				
FICO Score Decline between Origination and Modification		1.000	1.000	1.000	1.000				
	(missing FICO score decline indicator)	0.929	0.924	0.935	0.929				

Borrower Race/Ethnicity [REF: Non-Hispanic White]					
	Non-Hispanic Black	1.107	1.097	1.107	1.100
	Non-Hispanic Asian	0.885	0.919	0.906	0.924
	Non-Hispanic Other	0.732	0.718	0.720	0.716
	Hispanic	1.030	1.019	1.034	1.027
	(missing race/ethnicity)	1.110	1.101	1.111	1.108
Received Foreclosure Counseling before Modification		0.981	0.983	0.989	0.985
Neighborhood Characteristics					
House Price Appreciation (%)		1.266	1.310	1.274	1.293
Recent Foreclosure Rate [REF:<1]					
	1-2%	1.062	1.057	1.069	1.064
	2-3%	1.073	1.074	1.087	1.081
	>3%	0.986	0.995	1.003	1.002
Neighborhood Racial Composition [REF: 0-20%]					
% Non-Hispanic Black	20-40%	1.035	1.039	1.038	1.035
	40-60%	1.186	1.189	1.191*	1.188
	60-80%	0.980	0.968	0.981	0.971
	>80%	1.071	1.077	1.087	1.084
% Hispanic	20-40%	0.957	0.976	0.958	0.970
	>40%	0.978	0.996	0.985	0.994
% Non-Hispanic Asian	20-40%	0.987	0.971	0.985	0.978
	>40%	0.639	0.631	0.593	0.600
% Foreign Born [REF: 0-20%]					
	20-40%	1.011	1.026	0.997	1.015
	40-60%	0.930	0.940	0.921	0.934
	>60%	0.984	1.012	1.008	1.018
Median Household Income (1999) [REF: $40,000-60,000]					
	$0-20,000	0.795*	0.787*	0.792*	0.789*
	$20,000-40,000	0.980	0.979	0.986	0.985
	>$60,000	0.947	0.926	0.923	0.915
Unemployment Rate (%)		1.021*	1.019	1.018	1.018
Origination year [REF: 2004]					
	2005	1.207	1.188	1.217	1.201
	2006	1.224	1.182	1.211	1.191
	2007	1.160	1.105	1.152	1.121
	2008	1.135	1.047	1.043	1.026
Borough [REF: Queens]					
	Manhattan	1.144	1.090	1.116	1.089
	Bronx	0.932	0.914	0.919	0.912

	Brooklyn	1.090	1.076	1.077	1.074
Quarter of Loan Performance [REF: 2010 - 4]					
	2008 - 1	1.891	1.159	1.230	1.009
	2008 - 2	1.711	1.071	1.215	1.001
	2008 - 3	2.658***	1.647*	1.939**	1.580
	2008 - 4	3.485***	2.162***	2.634***	2.131***
	2009 - 1	3.814***	2.466***	3.048***	2.473***
	2009 - 2	2.408***	1.698***	1.969***	1.678***
	2009 - 3	2.991***	2.286***	2.552***	2.254***
	2009 - 4	2.501***	2.049***	2.228***	2.026***
	2010 - 1	1.657***	1.439***	1.542***	1.431***
	2010 - 2	1.273**	1.161	1.231**	1.163
	2010 - 3	1.277***	1.219**	1.252**	1.216**
Servicer fixed effects included					
Pseudo-R2		0.1146	0.1162	0.1146	0.1146
N		42,380	42,380	42,380	42,380

Notes:

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

** denotes results that are statistically significant at the 5 percentlevel

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

Table 4. Model with Temporal Variation of HAMP effect

Variable		Effects on hazard of re-default (odds ratios) M1b
Modification Features		
Pre-HAMP Time Trend		0.928***
Post-HAMP		1.038
Post-HAMP Time Trend		0.901***
HAMP		0.425***
Post-HAMP Time Trend X HAMP		1.041
Loan Characteristics		
Credit Class Non-Prime		1.132*
	(missing credit class indicator)	2.923***
Product Description [REF: FRM]		
	ARM 2/28	1.007
	ARM 3/27	0.869
	ARM (other)	0.771*
	Other	0.891
Interest Only at Origination		0.914
	(missing interest only indicator)	0.706
Full Documentation		1.080
	(missing full documentation indicator)	1.584
Product Group [REF: Conventional]		
	Government (FHA, VA)	1.146
	Conventional with PMI	0.821**
	Other	1.143
Relative Interest Rate after Modification (FRMs) [REF: <0]		
	0-1	1.411***
	1-2	1.394***
	2-3	1.415***
	>3	1.687***
	(missing interest rate indicator)	0.897
Relative Interest Rate after Modification (ARMs) [REF: <0]		
	0-2	0.759
	2-4	1.461**
	>4	1.750***

	(missing interest rate indicator)	0.732
Number of Months Post-Adjustment (ARMs) [REF: <0]		
	0-3	0.920
	4-6	1.222
	>6	0.956
Investor Type [REF: Private Investor]		
	GSE	1.239***
	Held in Portfolio	1.140
	(missing investor type indicator)	1.066
% Months the Loan was 60+ DPD before Modification X Origination Year		
	X 2004	1.012***
	X 2005	1.012***
	X 2006	1.010***
	X 2007	1.011***
	X 2008	1.019***
Lis Pendens Filed before Modification		1.047
Current LTV [REF: <80%]		
	80-100%	1.064
	100-120%	1.050
	>120%	1.147
	(missing LTV indicator)	4.616***
log (Current Unpaid Balance)		1.237**
Loan Age		0.996
Time since Modification		0.970**
Borrower and Property Characteristics		
Owner Occupier		0.914
Current FICO Score [REF: <560]		
	560-620	0.623***
	620-650	0.430***
	650-680	0.415***
	680-720	0.212***
	>=720	0.172***
	(missing FICO score)	0.533***
FICO Score Decline between Origination and Modification		1.000
	(missing FICO score decline indicator)	0.966
Borrower Race/Ethnicity [REF: Non-Hispanic White]		
	Non-Hispanic Black	1.090
	Non-Hispanic Asian	0.889
	Non-Hispanic Other	0.642

	Hispanic	1.019
	(missing race/ethnicity)	1.098
Received Foreclosure Counseling before Modification		0.996
Neighborhood Characteristics		
House Price Appreciation (%)		1.614*
Recent Foreclosure Rate [REF:<1]		
	1-2%	1.073
	2-3%	1.092
	>3%	0.999
Neighborhood Racial Composition [REF: 0-20%]		
% Non-Hispanic Black	20-40%	1.023
	40-60%	1.192*
	60-80%	0.984
	>80%	1.077
% Hispanic	20-40%	0.969
	>40%	0.975
% Non-Hispanic Asian	20-40%	0.990
	>40%	0.654
% Foreign Born [REF: 0-20%]		
	20-40%	1.020
	40-60%	0.933
	>60%	0.979
Median Household Income (1999) [REF: $40,000-60,000]		
	$0-20,000	0.793*
	$20,000-40,000	0.975
	>$60,000	0.947
Unemployment Rate (%)		1.021*
Origination year [REF: 2004]		
	2005	1.140
	2006	1.216
	2007	1.293
	2008	1.259
Borough [REF: Queens]		
	Manhattan	1.123
	Bronx	0.924
	Brooklyn	1.077
Quarter of Loan Performance [REF: 2010 - 4]		
	2008 - 1	0.182
	2008 - 2	0.199***

	2008 - 3	0.331**
	2008 - 4	0.528
	2009 - 1	0.728
	2009 - 2	0.568*
	2009 - 3	0.818
	2009 - 4	0.870
	2010 - 1	0.754
	2010 - 2	0.757**
	2010 - 3	0.994
Servicer fixed effects included		
Pseudo-R2		0.1125
N		42,380

Notes:

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

** denotes results that are statistically significant at the 5 percentlevel

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

Table 5. Models with Interactions between Modification Features and FICO and LTV

Variable		Effects on hazard of re-default (odds ratios)		
		M2b	M3b	M4b
Modification Features				
HAMP		0.665***	0.684***	0.713***
Monthly Mortgage Payment Change (pre— post mod, as % of pre mod)		0.984***		0.988***
	(missing payment change indicator)	1.104		1.045
Monthly Mortgage Payment Change X FICO<560		0.999		0.995
Monthly Mortgage Payment Change X LTV>100%		1.002		1.002
Principal Balance Change (pre— post mod, as % of pre mod)			0.992	0.998
	(missing balance change indicator)		1.231*	1.185
Principal Balance Change X FICO<560			0.999	1.001
Principal Balance Change X LTV>100%			0.982**	0.979**
Interest Rate Change (pre— post mod, in percentage points)			0.870***	0.934*
	(missing rate change indicator)		0.829**	0.910
Interest Rate Change X FICO<560			1.038	1.077**
Interest Rate Change X LTV>100%			1.017	0.981
Term Extension (Yes=1, No=0)			0.772**	0.846
	(missing term extension indicator)		1.017	1.050
Term Extension X FICO<560			0.919	0.954
Term Extension X LTV>100%			1.160	1.147
Loan Characteristics				
Credit Class Non-Prime		1.193**	1.145*	1.164**
	(missing credit class indicator)	3.137***	2.936***	2.985***
Product Description [REF: FRM]				
	ARM 2/28	1.043	1.056	1.057
	ARM 3/27	0.846	0.875	0.857
	ARM (other)	0.863	0.858	0.885
	Other	0.910	0.928	0.927
Interest Only at Origination		0.950	0.947	0.968
	(missing interest only indicator)	0.700	0.593*	0.659
Full Documentation		1.093	1.093	1.092
	(missing full documentation indicator)	1.832	2.058*	2.015*
Product Group [REF: Conventional]				
	Government (FHA, VA)	1.097	1.136	1.112
	Conventional with PMI	0.856*	0.837*	0.869
	Other	1.109	1.148	1.134
Relative Interest Rate after Modification (FRMs) [REF: <0]				
	0-1	1.119	1.191	1.106
	1-2	1.142	1.209	1.119
	2-3	1.150	1.222*	1.126
	>3	1.561***	1.541***	1.519***
	(missing interest rate indicator)	0.796*	0.832	0.824
Relative Interest Rate after Modification (ARMs) [REF: <0]				
	0-2	0.739	0.716	0.709
	2-4	1.229	1.301	1.208
	>4	1.574***	1.573***	1.521***
	(missing interest rate indicator)	0.812	0.768	0.818
Number of Months Post-Adjustment (ARMs) [REF: <0]				
	0-3	0.857	0.879	0.860
	4-6	1.120	1.129	1.103

	>6	0.870	0.872	0.855
Investor Type [REF: Private Investor]				
	GSE	1.231***	1.243**	1.240***
	Held in Portfolio	1.075	1.146	1.091
	(missing investor type indicator)	1.051	1.003	1.032
% Months the Loan was 60+ DPD before Modification X Origination Year				
	X 2004	1.011***	1.011***	1.011***
	X 2005	1.010***	1.010***	1.010***
	X 2006	1.008***	1.007***	1.007***
	X 2007	1.011***	1.010***	1.010***
	X 2008	1.017***	1.017***	1.017***
Lis Pendens Filed before Modification		1.040	1.042	1.021
Current LTV [REF: <80%]				
	80-100%	1.045	1.048	1.050
	100-120%	1.002	0.877	0.899
	>120%	1.082	0.912	0.941
	(missing LTV indicator)	4.479***	4.501***	4.452***
log (Current Unpaid Balance)		1.222**	1.211**	1.208**
Loan Age		0.991	0.989	0.989
Time since Modification		1.038***	1.047***	1.040***
Borrower and Property Characteristics				
Owner Occupier		0.914	0.914	0.914
Current FICO Score [REF: <560]				
	560-620	0.609***	0.639***	0.633***
	620-650	0.420***	0.441***	0.435***
	650-680	0.405***	0.432***	0.421***
	680-720	0.203***	0.219***	0.213***
	>=720	0.163***	0.169***	0.166***
	(missing FICO score)	0.564***	0.567***	0.575***
FICO Score Decline between Origination and Modification		1.000	1.000	1.000
	(missing FICO score decline indicator)	0.923	0.942	0.934
Borrower Race/Ethnicity [REF: Non-Hispanic White]				
	Non-Hispanic Black	1.097	1.106	1.095
	Non-Hispanic Asian	0.918	0.902	0.921
	Non-Hispanic Other	0.718	0.719	0.727
	Hispanic	1.021	1.036	1.025
	(missing race/ethnicity)	1.102	1.108	1.102
Received Foreclosure Counseling before Modification		0.982	0.989	0.983
Neighborhood Characteristics				
House Price Appreciation (%)		1.305	1.253	1.277
Recent Foreclosure Rate [REF:<1]				
	1-2%	1.056	1.074	1.067
	2-3%	1.073	1.090	1.085
	>3%	0.995	1.006	1.005
Neighborhood Racial Composition [REF: 0-20%]				
% Non-Hispanic Black	20-40%	1.039	1.038	1.033
	40-60%	1.188	1.175	1.168
	60-80%	0.968	0.973	0.960
	>80%	1.076	1.079	1.072
% Hispanic	20-40%	0.976	0.952	0.961
	>40%	0.996	0.975	0.977
% Non-Hispanic Asian	20-40%	0.970	0.987	0.972
	>40%	0.632	0.598	0.605

% Foreign Born [REF: 0-20%]				
	20-40%	1.026	0.997	1.017
	40-60%	0.939	0.919	0.935
	>60%	1.014	1.006	1.016
Median Household Income (1999) [REF: $40,000-60,000]				
	$0-20,000	0.786*	0.795*	0.795*
	$20,000-40,000	0.980	0.988	0.987
	>$60,000	0.926	0.916	0.911
Unemployment Rate (%)		1.019	1.019	1.019
Origination year [REF: 2004]				
	2005	1.188	1.227	1.208
	2006	1.181	1.219	1.189
	2007	1.100	1.153	1.114
	2008	1.041	1.031	1.008
Borough [REF: Queens]				
	Manhattan	1.090	1.101	1.063
	Bronx	0.914	0.921	0.915
	Brooklyn	1.076	1.081	1.080
Quarter of Loan Performance [REF: 2010 - 4]				
	2008 - 1	1.154	1.147	0.944
	2008 - 2	1.063	1.150	0.955
	2008 - 3	1.633*	1.867**	1.533
	2008 - 4	2.147***	2.565***	2.091***
	2009 - 1	2.457***	2.987***	2.427***
	2009 - 2	1.696***	1.943***	1.664***
	2009 - 3	2.284***	2.516***	2.229***
	2009 - 4	2.049***	2.213***	2.022***
	2010 - 1	1.440***	1.533***	1.424***
	2010 - 2	1.162	1.226*	1.158
	2010 - 3	1.220**	1.248**	1.212**
Servicer fixed effects included				
Pseudo-R2		0.1163	0.1149	0.1149
N		42,380	42,380	42,380

Notes:

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

** denotes results that are statistically significant at the 5 percentlevel

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

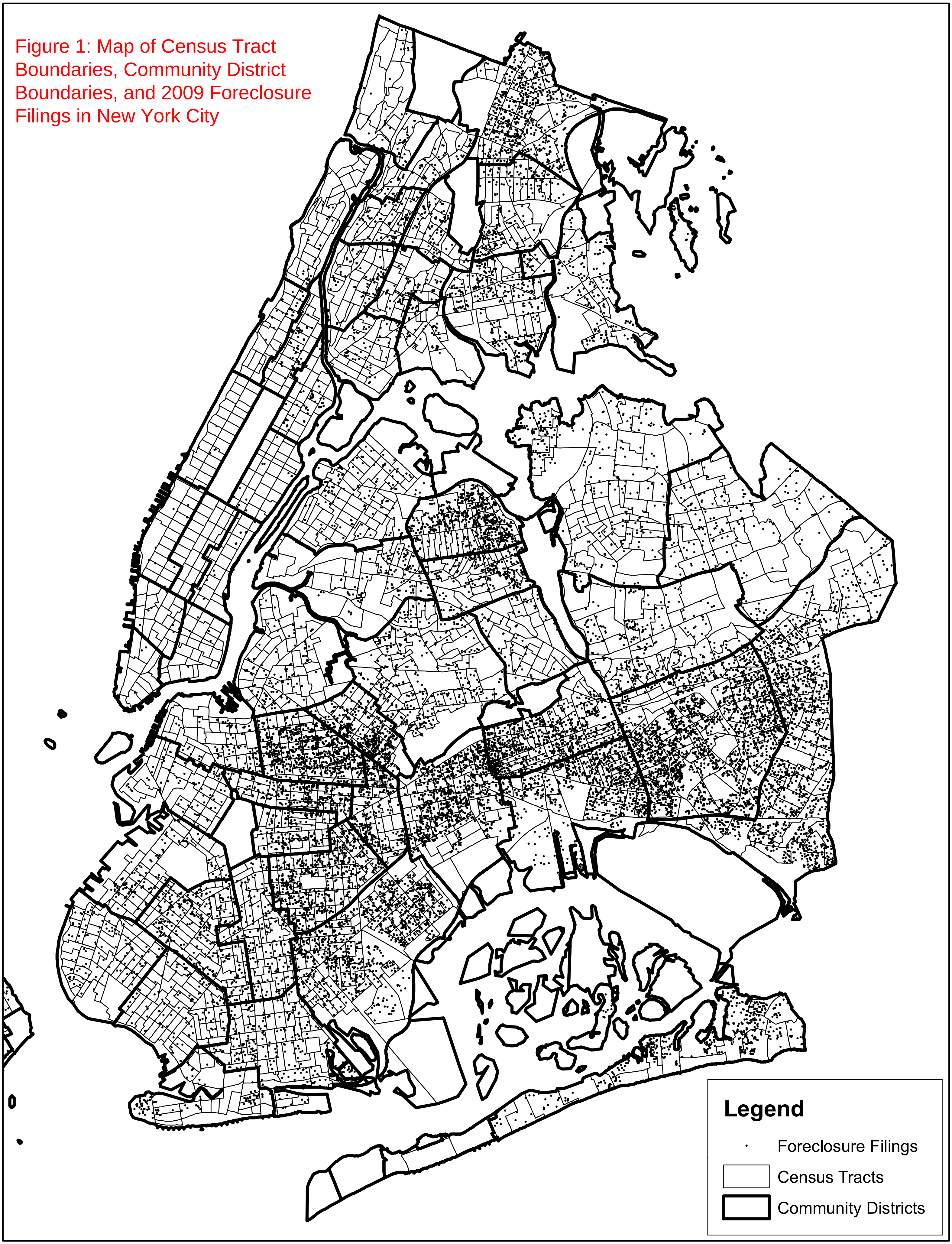


Figure 1: Map of Census Tract Boundaries, Community District Boundaries, and 2009 Foreclosure Filings in New York City
Legend
Foreclosure Filings
Census Tracts
Community Districts

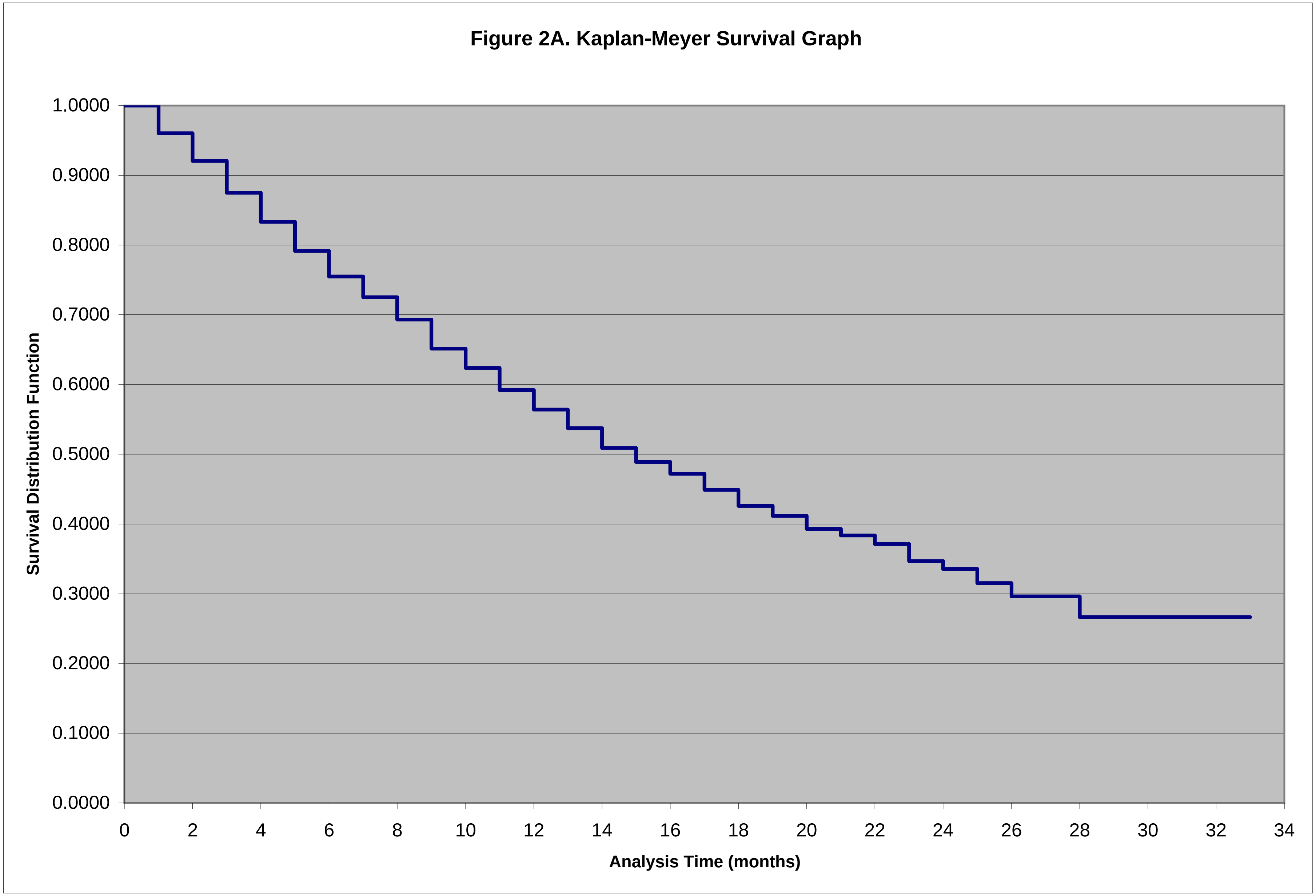


Figure 2A. Kaplan-Meyer Survival Graph
Survival Distribution Function
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
0
2
4
6
8
10
12
14
16
18
20
22
24
26
28
30
32
34
Analysis Time (months)

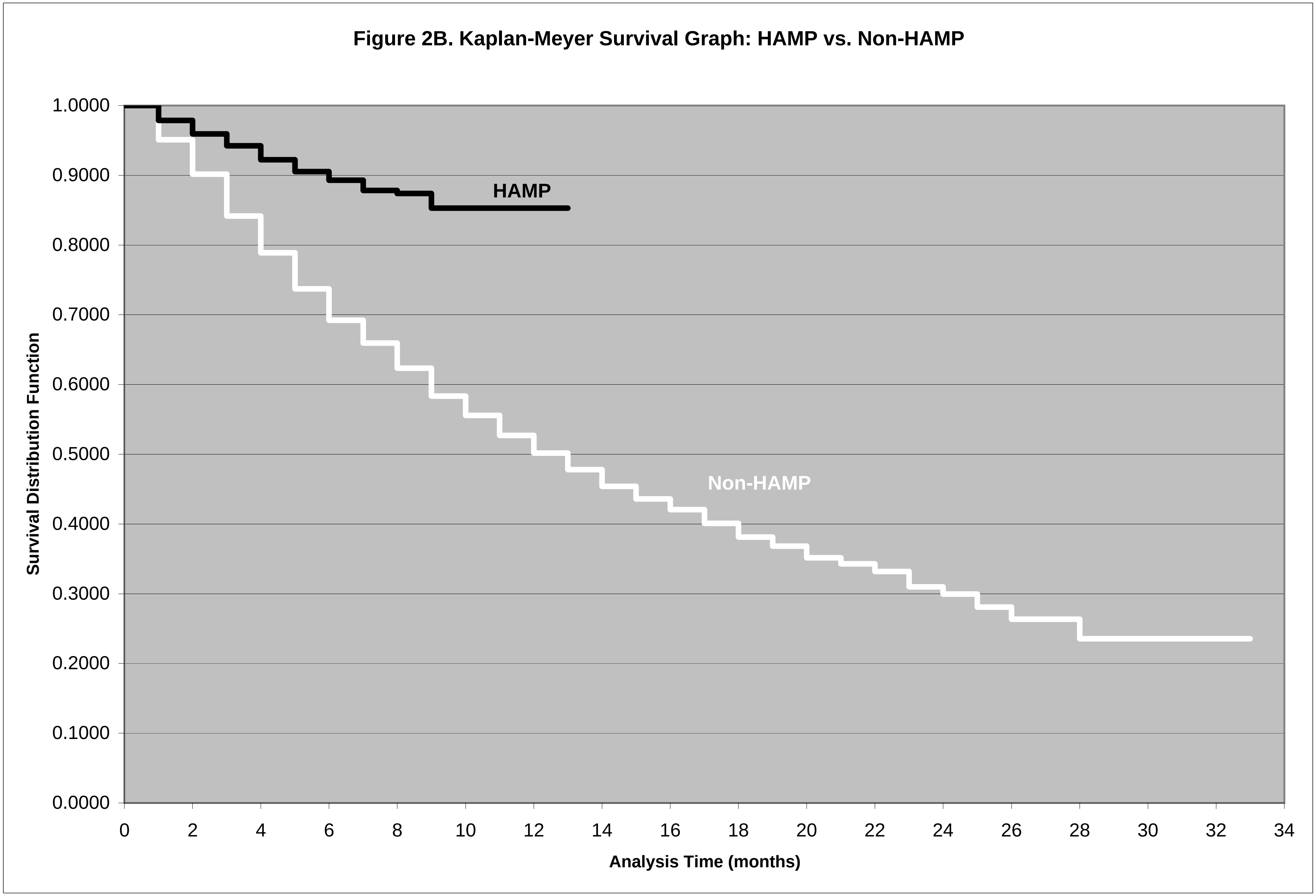
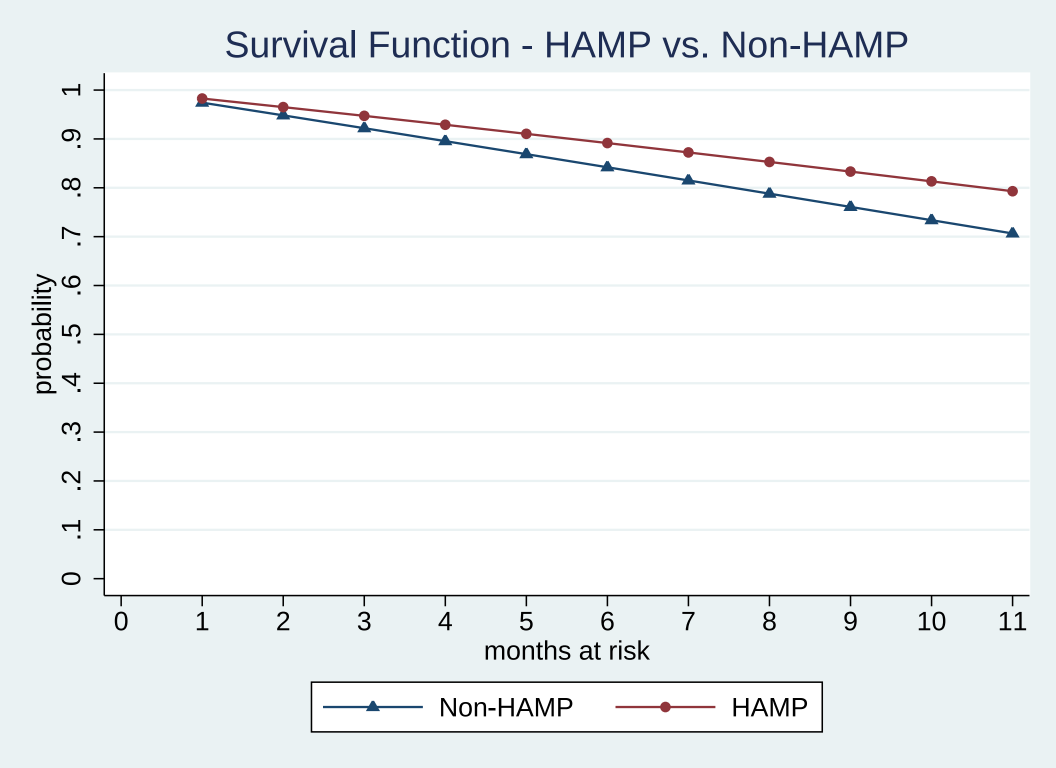
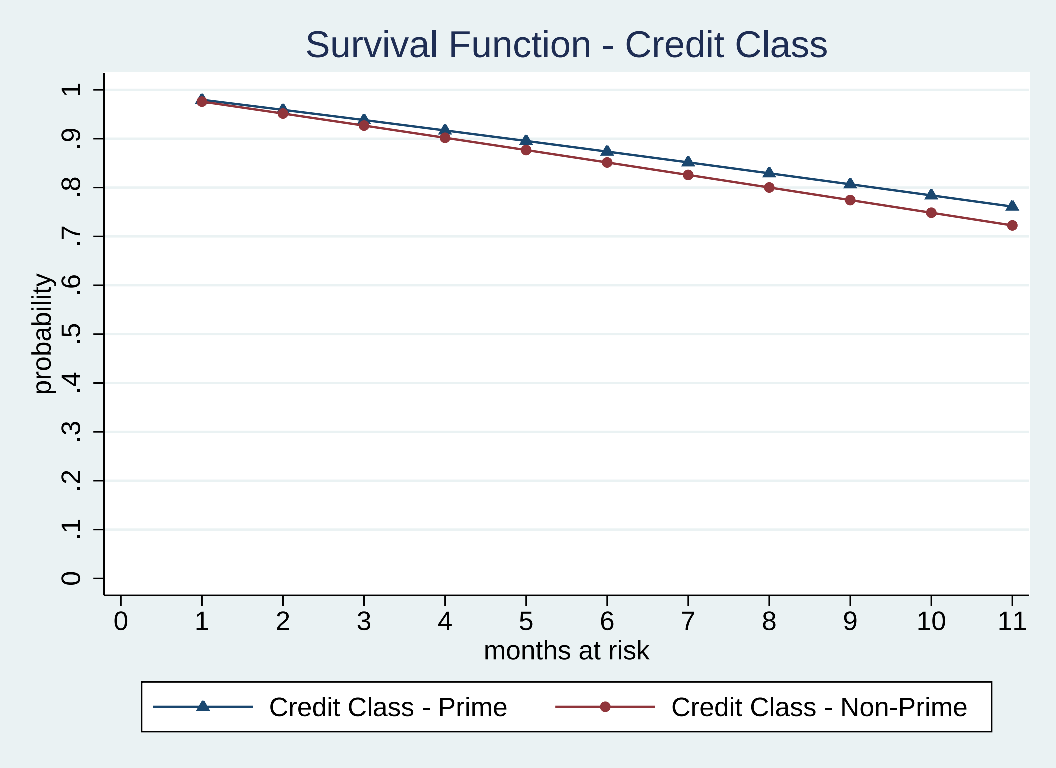


Figure 2B. Kaplan-Meyer Survival Graph: HAMP vs. Non-HAMP
Survival Distribution Function
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
HAMP
Non-HAMP
0
2
4
6
8
10
12
14
16
18
20
22
24
26
28
30
32
34
Analysis Time (months)

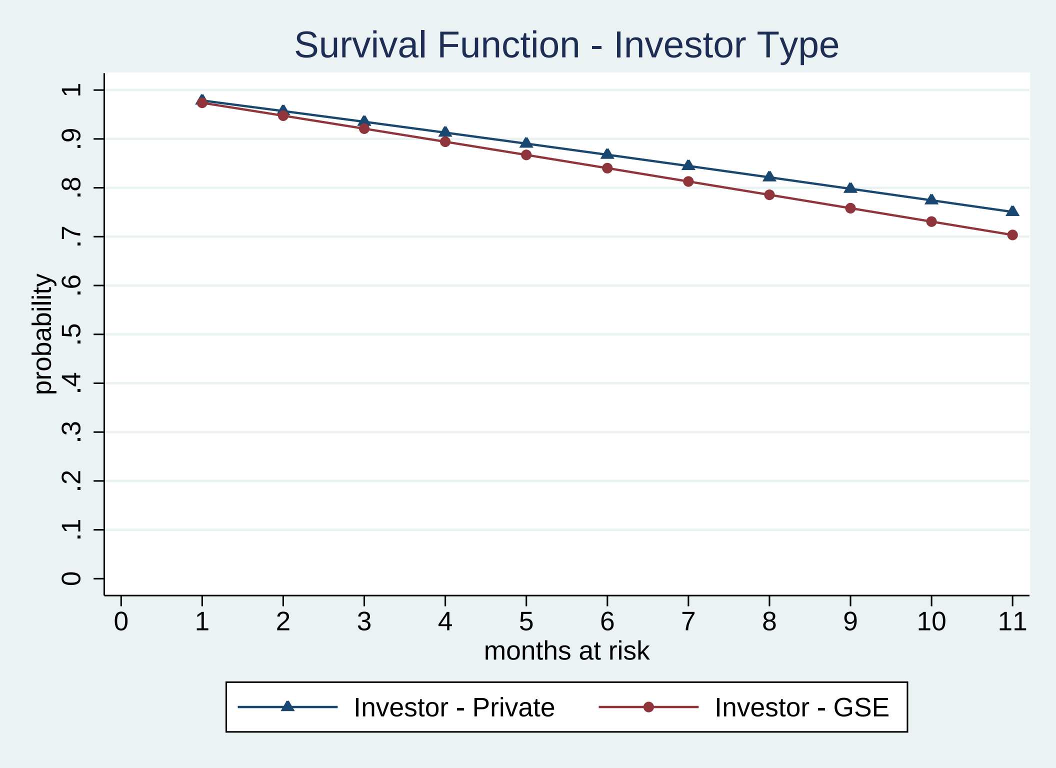
Figure 3. Effects of Selected Variables on the Survival Function

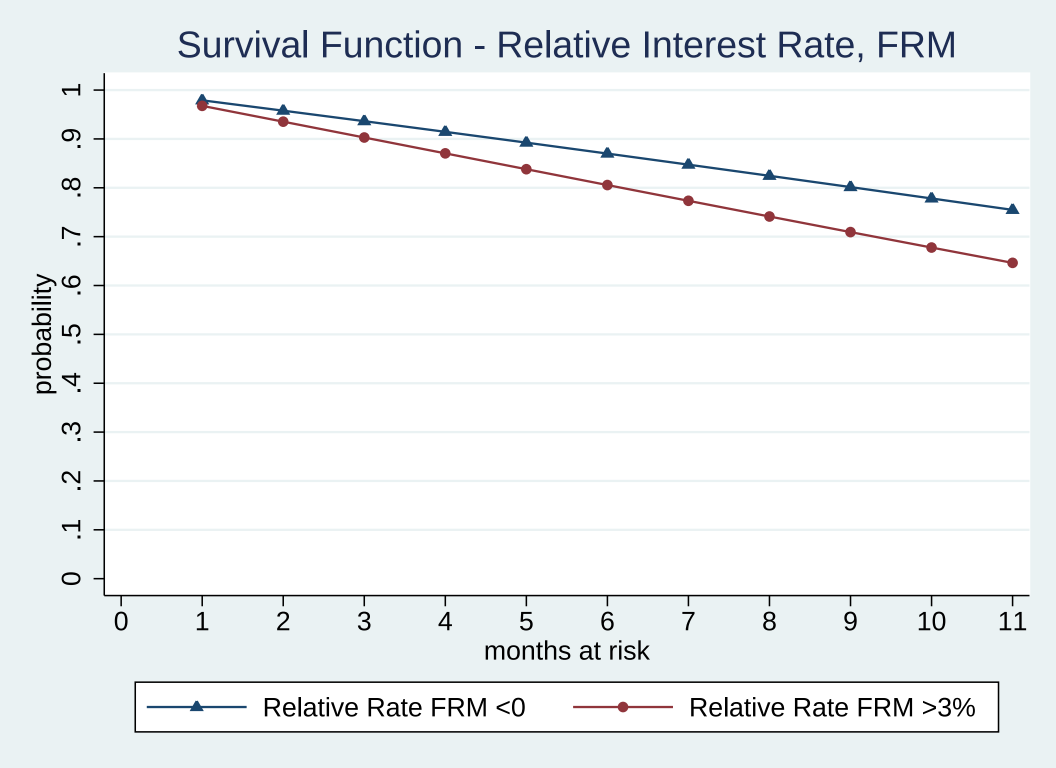


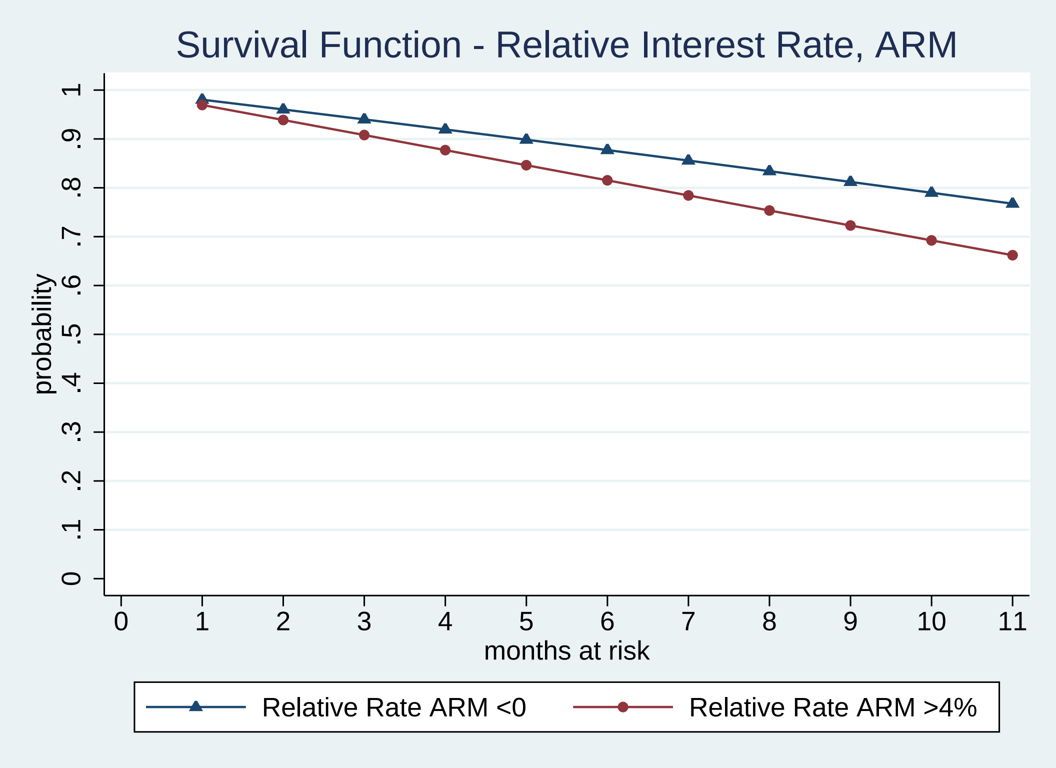
Survival Function - HAMP vs. Non-HAMP
probability
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0
1
2
3
4
5
6
7
8
9
10
11
months at risk
Non-HAMP
HAMP

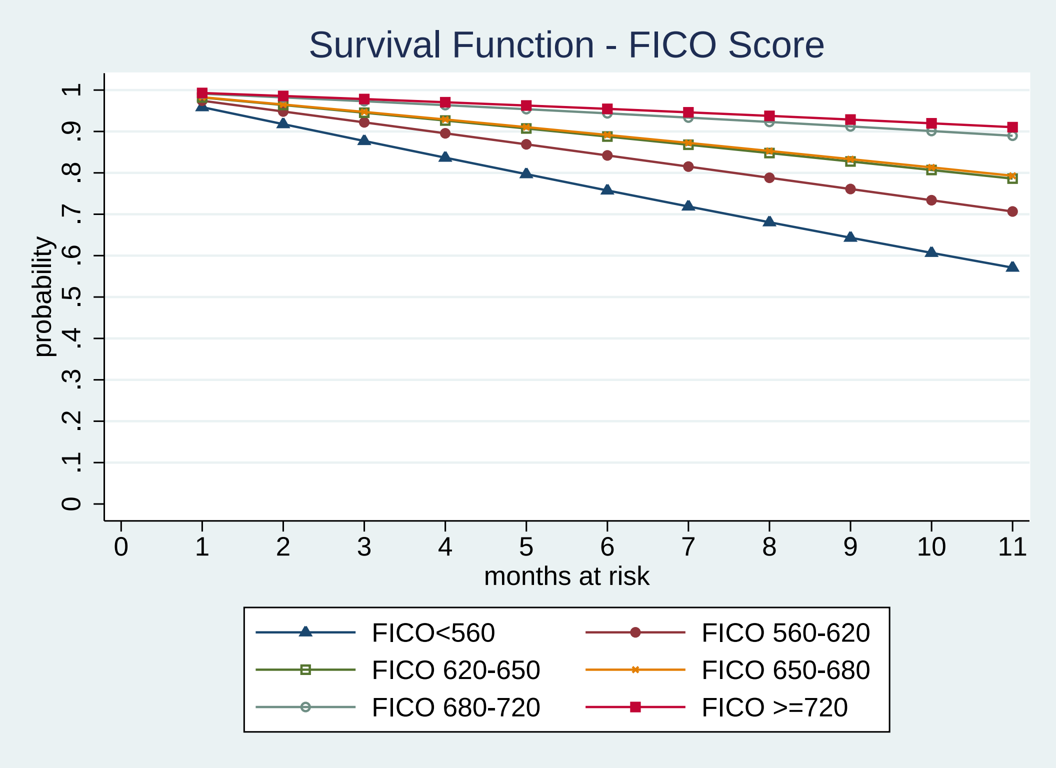


Survival Function - Credit Class
probability
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0
1
2
3
4
5
6
7
8
9
10
11
months at risk
Credit Class - Prime
Credit Class - Non-Prime


Survival Function - Investor Type
probability
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0
1
2
3
4
5
6
7
8
9
10
11
months at risk
Investor - Private
Investor - GSE


Survival Function - Relative Interest Rate, FRM
probability
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0
1
2
3
4
5
6
7
8
9
10
11
months at risk
Relative Rate FRM <0
Relative Rate FRM >3%


Survival Function - Relative Interest Rate, ARM
probability
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0
1
2
3
4
5
6
7
8
9
10
11
months at risk
Relative Rate ARM <0
Relative Rate ARM >4%



Survival Function - FICO Score
probability
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
0
1
2
3
4
5
6
7
8
9
10
11
months at risk
FICO<560
FICO 560-620
FICO 620-650
FICO 650-680
FICO 680-720
FICO >=720