

The Limited Benefits of Mortgage Renegotiation

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Abstract

During the housing crisis regulators faced impediments in their unprecedented intervention to promote large-scale mortgage renegotiation. What hampered renegotiation in the wake of the crisis? To answer this question, I study the expected gains from renegotiation to both sides of a mortgage contract: investors and borrowers. To overcome selection bias, I use plausibly exogenous variation in the propensity of intermediaries to renegotiate mortgages. I find that loan modification helped investors recover only 2.4% more of the principal balance outstanding at the time of delinquency relative to foreclosing upon the borrower. However, there was substantial variation around this mean—a 11.8% (4.8 times the mean) standard deviation—which highlights the high degree of uncertainty about the realization of these gains. Thus, despite expected gains to borrowers—higher credit scores and a \$115 increase in monthly consumption—regulators’ attempts to promote mortgage renegotiation have proven to be ineffective, exacerbating debt overhang and its consequences.

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I have long advocated a systematic and streamlined approach to loan modification that puts borrowers into long term, sustainable mortgages. I support the industry plan as a means to allow borrowers to remain in their homes, provide investors with higher returns than can be obtained under foreclosure, and strengthen local neighborhoods where foreclosures are already driving down property values. It is my hope that this plan will be implemented in a way that delivers real progress on these important policy goals.

- Sheila Bair, Chairman of FDIC, in foreword to The Case for Loan Modification

1 Introduction

During the housing crisis, thousands of borrowers were unable to make the monthly payments on their mortgages and became seriously delinquent, with significant consequences on the broader economy (Mayer et al. (2009), Palmer (2015), Mian and Sufi (2009), Mian et al. (2013), Mian and Sufi (2014)). At the onset of the crisis, regulators such as FDIC Chairman Sheila Bair strongly promoted widespread mortgage renegotiation, although others were hesitant to do so, citing concerns about strategic behaviour by borrowers (Mayer et al. (2014)). Academic economists and legal scholars alike put forth proposals to encourage renegotiation (Posner and Zingales (2009), Mayer et al. (2009)). Eventually, regulators initiated an unprecedented intervention in debt markets to encourage loan modification, but they remained disappointed by its efficacy. Agarwal et al. (2016) show that the flagship Home Affordable Modification Program (HAMP) resulted in permanent modifications of only about 15% of all delinquent loans. In fact, towards the end of 2009, the Obama administration began to apply pressure on mortgage companies to ramp up loan modifications.¹

Ultimately, the completion of renegotiation will depend on whether the expected gains available to the agents on *both* sides of this debt contract are sufficient to induce them to participate.² Surprisingly, despite significant government resources being directed to encourage mortgage debt renegotiation, little work has been done to understand whether these gains were in fact achievable. Understanding these gains is crucial to appropriately design market interventions. For programs such as HAMP to be more successful, is it constraints on

¹“After months of playing pretend, the Treasury Department conceded last week that the Home Affordable Modification Program, its plan to aid troubled homeowners by changing the terms of their mortgages, was a dud.” – New York Times, December 6th, 2009. “The Obama administration on Monday plans to announce a campaign to pressure mortgage companies to reduce payments for many more troubled homeowners, as evidence mounts that a \$75 billion taxpayer-financed effort aimed at stemming foreclosures is foundering.” – New York Times, November 29th, 2009.

²While debt renegotiation may have positive externalities—e.g. reducing the externalities that arise from foreclosure Campbell et al. (2011)—these are unlikely to be internalized by privately optimizing agents on either side of the mortgage contract.

borrowers or investors that need to be relaxed? To shed light on the decision to renegotiate debt, I estimate the expected gains from modification relative to immediate foreclosure to both sides of the contract—the investor and the borrower.

My results show that there was likely little resistance from borrowers to the renegotiation of debt. However, the participation constraint of investors were often not met due to relatively small gains and a high variance around these gains. Previous explanations, both theoretical and empirical, for the perceived low rate of debt renegotiation have revolved around agency problems in securitization (Agarwal et al. (2011), Piskorski et al. (2010), Moordian and Pichler (2013), Kruger (2015), Thompson (2011), Agarwal et al. (2014), Levitin and Twomey (2011)) or adverse selection (Adelino et al. (2013a), Adelino et al. (2013b)). Using the findings of this literature to motivate an appropriate empirical strategy, I provide evidence for an alternative channel which held up renegotiation. My findings complement the above literature by demonstrating that even in the absence of such agency problems renegotiation may have been subdued because of low expected gains to investors.

Quantifying the effect of renegotiation on the number of monthly payments completed by the borrower is vital to estimate the expected gains to investors from debt renegotiation. I determine the mean and the variance of the expected gains from renegotiation by combining an estimate of this effect with assumptions about house prices and discount rates. Expected gains from renegotiation are defined as the present value of the incremental cash flows that arise when a mortgage is renegotiated relative to those that arise when it is not. The higher the number of monthly payments completed by the borrower, the longer the time to re-default, and the more the investor gains from the modification. Continued mortgage payments maintain amortization and reduce the probability of subsequent foreclosure. Loan modification, however, delays the terminal cash flow from the mortgage, imposing a time-value-of-money related cost on the investor.³

The challenge to estimating this causal effect arises because loans are not randomly renegotiated, as highlighted in the following example. Suppose two identical groups of borrowers become delinquent because they lose their jobs and cannot afford their monthly payments. Now suppose one group is able to obtain a renegotiation because, unobservable to the econometrician, they line up new jobs and can credibly promise to remain current. They would continue to make a large number of monthly payments. Those who do not get a renegotiation make two or three additional monthly payments but eventually end up in foreclosure. A naive comparison of the means of their outcome variables would result in an upward biased

³Note that some investors may have been protected by mortgage insurance, which would absorb a portion of the losses from foreclosure and liquidation. I abstract away from protection from insurance in the analysis. However, I note that any protection to investors would have made modifications even less desirable to them.

estimate of the causal effect of renegotiation precisely because it is not randomly given to borrowers.⁴ Hence, to overcome the endogeneity concern in this simple context, I require a variable, or a set of variables, that are correlated with whether a borrower receives a modification, but uncorrelated with whether a borrower is able to find employment.

To overcome such selection bias, I use a unique feature of the mortgage market; namely that the mortgage is monitored not by the investor, but by a third party, the mortgage servicer. In this market the servicer has discretion over the decision to renegotiate. I then draw upon the results of [Mooradian and Pichler \(2013\)](#), who theoretically model the consequences of the agency problem between the investors and the servicer, and [Agarwal et al. \(2011\)](#), [Piskorski et al. \(2010\)](#), [Kruger \(2015\)](#), [Reid \(2015\)](#), [Agarwal et al. \(2016\)](#), and [Korgaonkar \(2016\)](#) who provide evidence that this agency problem manifests itself in substantial heterogeneity across servicers in their propensity to modify mortgage debt. This motivates the use of such variation to instrument for whether a loan gets modified.⁵

Two aspects of the market validate this strategy. First, borrowers do not choose who their mortgage servicers are, mitigating concerns about endogenous selection of borrowers into servicers. Second, borrowers are unlikely to be aware of their servicer’s propensity to modify a mortgage, how this propensity compares to other servicers, and why such variation arises in the first place. Thus, conditional on observables, this variation will be exogenous to a borrower’s decisions to make an additional monthly payment. In the context of the simple example constructed above, the identity of the borrower’s servicer will be unrelated to whether the borrower finds a job or not.

First, I show that loan modification predicts the completion of 56 additional monthly payments by the borrower. Given this finding, the present value of gains to investors from modification relative to foreclosure amounts to about 2.4% of the outstanding balance at entry into serious delinquency. This equates to about \$4900 for the average balance of \$202,700. Not only are the expected gains from modification relatively low, but there is also substantial variation around them. From the perspective of the investor who observes key characteristics of the loan pool⁶, the standard deviation of these gains is 11.8% (i.e., 4.8 times the mean). This variation is larger than that resulting from spatial variation over time

⁴The bias may go the other way as well. For example, if the servicer knows that a borrower will be re-employed he might not give him a modification as he will be able to self-cure. In this case, the naive estimate of causal effect of loan modification will be biased downwards. Such selection biases arise because I cannot observe the counterfactual outcome for those borrowers who received or did not receive a loan modification.

⁵In practice, I implement the first stage of a two-staged least squares by using either servicer-by-time-of-delinquency fixed effects or servicer-by-time-since-delinquency fixed effects to predict whether a loan receives a modification or not.

⁶These will include borrowers credit score, property value and loan-to-value-ratio at origination, the location of the property and the timing of the delinquency.

time series (5.8% across-CBSA-by-time standard deviation) which highlights the importance of borrower-specific heterogeneity.⁷ Overall, the participation constraints of investors were just about met, if investors were risk neutral, and are unlikely to have been met if they were risk-averse.

The failure of the investor’s participation constraint to hold will be sufficient to preclude debt renegotiation. This suggests that contracting frictions are not the only impediment to debt renegotiation in mortgage markets. Insufficient gains to investors may have precluded debt renegotiation even without such frictions. Moreover, while it is important to align the incentives of servicers and investors, or subsidize servicers’ costs of making loan modifications, interventions to encourage renegotiation must ensure that investors are willing to participate in the first place.

Given these results, if gains from renegotiation do exist for the other side of the contract—the borrower—they would remain unrealized. Whether these gains are available is ultimately an empirical question. A policy decision on whether to intervene, and whose constraints the intervention should lift will rest on the answer to this question. In a result that is novel to the literature on mortgage renegotiation, I show that borrowers increase consumption by \$115 per month following loan modification, which amounts to \$5,700 in present value terms.⁸ Investors’ failure to renegotiate loans fails to alleviate liquidity constraints on borrowers, distorting their consumption and keeping them in serious delinquency.

My paper is related to a broader literature understanding and assessing countercyclical policies employed in the wake of the financial crisis. Unconventional monetary policy had a profound impact on housing and mortgage markets through the large-scale asset purchases of the quantitative easing program, which lowered mortgage rates and fueled refinancing activity.⁹ However, it was only the most credit-worthy borrowers who benefitted from these policies.¹⁰ The government also intervened more directly to assist borrowers who were current on their mortgages but deeply underwater and so unable to obtain a refinancing. This took the form of the Home Affordable Refinancing Program (HARP), whose effect on interest rates and refinancing volume was mitigated by a flawed design which introduced competition

⁷The unconditional standard deviation of these gains is about 19%.

⁸Assuming discount rate of 4.9% in annual terms. This assumption is based on the average interest rates on 30 Year Fixed Rate mortgages at time of modification. In related work, [Ganong and Noel \(2017\)](#) estimate the marginal propensity to consume out of principal reductions, and find that borrowers are insensitive to changes in long-term obligations, but respond more to modifications that relax binding short-term constraints.

⁹[Krishnamurthy and Vissing-Jorgensen \(2011\)](#) document that Q.E.1 lowered prepayment risk borne by investors, and [Fuster and Willen \(2010\)](#) show that lenders passed this decrease onto borrowers by lowering mortgage rates.

¹⁰See [Beraja et al. \(2015\)](#) and [Di Maggio et al. \(2016\)](#) for a study of the real effects of quantitative easing and an examination of which borrowers and regions did or did not benefit from the program.

related distortions into the mortgage market.¹¹ This literature has often studied the impact of such policies on borrowers, ignoring equally important entities in any securitized credit market—the investors.

Yet another attempt to mitigate the fallout from the housing crisis involved renegotiating mortgages of borrowers who were unable to make monthly payments and faced foreclosure.¹² While mortgage renegotiation was observed prior to the government intervention in the form of the Home Affordable Modification Program (HAMP), several papers argued that the low rates of loan modification were due to agency problems and distorted incentives within the securitization chain.¹³ My findings complement this literature and suggest an alternative channel that prevented mortgage modification—insufficient gains to investors.

In addition to further understanding the efficacy of loan modifications as a response to the housing crisis, my paper builds upon the work of [Maturana \(2016\)](#) and [Agarwal et al. \(2016\)](#) who describe the ex-post effects of loan modification. [Maturana \(2016\)](#) studies the ex-post realized losses on privately securitized loans and finds that renegotiated loans had lower realized losses. First, this paper does not provide a view of the gains available to investors at the time at which the mortgage becomes delinquent, which is the relevant metric to understand the decision to renegotiate. The mean and variance of the gains I estimate fill this gap and provide this perspective. Moreover, this leaves us with an incomplete view as his results do not account for potential gains and losses to those on the other side of the contract, the borrowers.

[Agarwal et al. \(2016\)](#) demonstrate that geographies where servicers were more likely to modify loans experienced smaller house price declines, lower rates of delinquency on non-mortgage debt and higher levels of automobile purchases. While these results are informative of the social benefits of debt renegotiation and so justify intervention on the basis of realizing these externalities, they do not tell us about why such intervention would be needed in the first place. My results show that investors' limited gains made them unlikely to want to modify, which in turn pushed the government to intervene in this large debt market.

The rest of the paper proceeds as follows. Sections 2 to 5 estimate and discuss the gains to investors from renegotiation. Section 2 lays out a simple conceptual framework to inform the empirical analysis, Section 3 outlines the empirical frameworks used to, Section 4 describes

¹¹[Amromin and Kearns \(2014\)](#) and [Agarwal et al. \(2015\)](#) study the effects of HARP on refinancing and show that the program changed the competitive landscape of the refinancing market with adverse effects on both interest rates and the volume of refinancing.

¹²[Eberly and Krishnamurthy \(2014\)](#) provide a simple framework to conceptualize the tradeoffs between renegotiating a loan or not and describe loan modifications that may be optimal.

¹³Most recently [Agarwal et al. \(2016\)](#) suggest that pre-existing institutional frictions related to the operating capacity and infrastructure of mortgage services may have impeded the success of HAMP.

the sources of data used, and Section 5 presents the estimate of the gains. Having established the main result, Section 6 describes the data, methodology and the results of the test for the presence of gains to borrowers. Section 7 discusses robustness checks and extensions and Section 8 concludes.

2 Conceptual Framework

A mortgage contract is a complex instrument. The cash flows that it generates to investors and the utility that it gives borrowers will be driven by several micro- and macro-economic factors. This section builds a simple conceptual framework to highlight the key quantities I need to estimate from the data in order to measure gains to investors, and to draw attention to assumptions I make in the subsequent analysis. A more detailed description of the framework appears in Appendix B.

2.1 Servicing of mortgage debt

One of the unique features of the mortgage market is the mechanism in place for post-origination monitoring of the debt. Neither the originator (lender) nor the investors in a securitized mortgage transaction maintain a relationship with the borrower after the issuance of the mortgage debt. A third party—the mortgage servicer—maintains a direct relationship with the borrower, obtaining monthly payments of principal and interest and passing them onto investors. The mortgage servicer is an agent of the securitization trust. His actions and duties are governed by the pooling and servicing agreement (PSA), the contract in place between the servicer and the trust. The servicer, not the lender or investor, has discretion over whether the mortgage gets renegotiated or not.

In modeling the servicer’s decision to renegotiate the loan, I assume that the servicer shares the investor’s objective function and seeks to maximise cash flows from the mortgage pool that collateralizes the bonds held by the investor.¹⁴ Making this assumption allows me to focus on estimating the gains to the investor from renegotiation rather than modeling the compensation structure of servicers. Additionally, I posit the existence of additional components specific to each servicer’s objective function that drive a wedge between it and

¹⁴Hunt (2009) surveys a representative sample of private label PSAs. He finds that the most common condition placed on a servicer contemplating renegotiation, is that the servicer act in the best interest of certificate-holders. Also note that in practice, there may be multiple investors who hold the bonds that are collateralized by the loan pool. I assume there is one representative investors who receives all the cash flows from a particular mortgage.

that of the investor. Thus, there will be some variation around this assumption, which I can use to my advantage to identify the effects of renegotiation. I discuss this further in Section 3.2.¹⁵

2.2 Representation of gains to investors

By assuming a shared objective function between investors and servicers I need only then model the cash flows to the investor to conceptualize the source of their gains.¹⁶ To focus attention on the key variables, first consider a simple setting with two periods ($t = 0, 1, 2$), and without asymmetric information, uncertainty or discounting of cash flows. A borrower looking to purchase a home worth P_0 borrows an amount D at $t = 0$. The mortgage contract is structured as a payment of interest in the first two periods ($d_1 = d_2 = d$) followed by the return of principal (D) at the end of $t = 2$.¹⁷

At $t = 1$ I assume that the borrower faces an unanticipated permanent income shock leaving him with insufficient resources to make the payment d .¹⁸ Once the borrower enters this serious delinquency (90+ days; i.e. three or more missed payments) the mortgage servicer may either renegotiate the loan or decide to foreclose upon the borrower.

A servicer may simply choose to forego any attempt to renegotiate the loan and foreclose upon the borrower, selling the property at a discount in a foreclosure sale (Campbell et al. (2011)) to recover principal for the investor. In this case, the investor receives $V(0) = \phi P_1$, where $1 - \phi \in (0, 1)$ is the discount.

Alternatively, a servicer may choose to renegotiate the mortgage. The servicer adjusts the terms of the contract to relax the borrower's liquidity constraint, allowing him to continue making payments d . In this simple setting, I model the modification as a change in the payment d to $d + \Delta$, where $\Delta < 0$, such that the borrower can become current on the mortgage. A modification may also involve a change to D , the principal due at $t = 2$.

¹⁵Such variation will not be a concern for the subsequent reduced form analysis of the causal effect of loan modification if I restrict attention to dependent variables which, in the absence of modification, are independent of the identity and practices of the servicer.

¹⁶The other side of this contract, of course, is the borrower, who will be discussed further in Section 6.

¹⁷Note that the possibility of default is not considered here. One can assume the borrower has no initial wealth and borrows at 100% Loan-to-Value ratio. One can assume then, that without a change in house prices, he repays this at the end of $t = 2$ by selling the property.

¹⁸This formulation captures the inherent incompleteness of a mortgage contract. In this setting, given the assumed lack of ex-ante uncertainty, the contract will be non-contingent when originated. I follow Eberly and Krishnamurthy (2014) in modeling the unexpected income shock to capture such incomplete contracting frictions in a reduced form manner. Inherent in such set-up is the assumption that the borrower does not default due to a fall in collateral value but rather due to a liquidity shock.

A careful understanding of the loan’s performance following the modification is crucial to measuring the gains to investors.¹⁹ I assume two possibilities to reflect the data. Following loan modification, the borrower either remains current and continues to pay the mortgage; either until it is paid in full or until he can prepay the loan. Alternatively, he may re-enter delinquency and be foreclosed upon.

Both these events represent a return of principal to the investor at some future date. I model this terminal cash flow in a reduced form manner using the function $G(P, D)$ which depends on the property value and the amount of principal outstanding.²⁰ Thus following modification an investor’s cash flows are $V(\Delta) = d + \Delta + d + \Delta + G(P_2, D_2)$.

I conceptualize the gains to the investor as the present value of the expected cash flows that arise when a loan is renegotiated relative to when it is not. The gains are represented by:

$$V(\Delta) - V(0) = \underbrace{d + d + \Delta + \Delta + G(D, P_2)}_{\text{Renegotiated}} - \underbrace{\phi P_1}_{\text{Foreclosed}} \quad (1)$$

Equation 1 highlights how loan modifications change the stream of cash flows expected to accrue to investors. Investors receive additional payments from a renegotiated loan, $(2 \times d)$, which they would not have under foreclosure. However, these payments are smaller by amount $(2 \times \Delta)$ so as to assist borrowers in becoming current. Modification also changes the amount of principal recovered upon termination of a loan— $G(D, P_2)$ compared to ϕP_1 —and delays when it is recovered— $t = 2$ instead of $t = 1$.

Any methodology to estimate the gains defined in this manner must capture these varied effects. The next section lays out my approach to do so.²¹

2.3 Translating the framework to data

The empirical setting consists of additional intricacies that were left out of the conceptual framework. This section explains how Equation (1) maps to what I observe in the data.

In the empirical setting there will be variation in the number of payments that borrowers complete following their entry into delinquency, depending on whether or not their loan gets modified. Let T_{Mod} denote the expected number of payments completed by the borrower if

¹⁹See [Ambrose and Capone \(1998\)](#), and [Ambrose and Capone \(2000\)](#) for earlier studies on more refined methodologies of modeling post delinquency loan performance

²⁰More specifically, I assume $G(P, D) = \mathbf{1}_{\{0.9 \times P < D\}} \cdot \phi P + \mathbf{1}_{\{0.9 \times P \geq D\}} \cdot D$. Formulating it in this way allows me to match the average rate of post modification re-default in the data.

²¹The discussion here does not consider the preferences of the borrower, and the sources of any gains to them. This is discussed in detail in Appendix Section B and in Section 6.

his mortgage is modified following entry into serious delinquency, and T_{NoMod} be the expected number of payments completed if it is not modified. $T_{NoMod} \geq 0$ either because the borrower attempts to recover from the delinquency, or because he self-cures and continues to make payments on his mortgage (Ambrose and Capone (1998)). The mortgage remains active until $t = 1 + T_{Mod}$ if modified and $t = 1 + T_{NoMod}$ if not modified.

Adding uncertainty about the realization of house prices to the framework above requires me to make an assumption about how these prices evolve. I assume $E_1[P_{1+k}] = P_1$ for all k ; i.e., that house prices follow a random walk. Making this assumption, I only need to estimate the property value at the time of the borrower's entry into serious delinquency. Finally, I incorporate discounting into the framework, assuming that all cash flows from $t > 1$ onwards will be discounted at rate R_1 .

I decompose the gains from renegotiation into those which arise from the present value of continued payments by the borrower due to loan modification, denoted $\Delta PV(\text{PMTs})$; and those from the present value of gains from termination of the mortgage contract, denoted $\Delta PV(\text{Termination})$. These can be calculated as:

$$\Delta PV(\text{PMTs}) = \sum_{k=1}^{T_{Mod}} \frac{d + \Delta}{(1 + R_1)^k} - \sum_{k=1}^{T_{NoMod}} \frac{d}{(1 + R_1)^k} \quad (2)$$

$$\Delta PV(\text{Termination}) = \frac{G(P_1, D_{T_{mod}})}{(1 + R_1)^{T_{mod}}} - \frac{\phi P_1}{(1 + R_1)^{T_{NoMod}}} \quad (3)$$

where $V(\Delta) - V(0) = \Delta PV(\text{PMTs}) + \Delta PV(\text{Termination})$.²² To estimate $(V(\Delta) - V(0))_i$ for each loan in the sample, I require estimates of $T_{i,Mod}$ and $T_{i,NoMod}$. They can be obtained by estimating a model of the causal effect of loan modification on the number of monthly payments completed by the borrower and using predicted values from this model (see Section 3.1). For renegotiated mortgages, I have data on how each of the contract terms change as a result of the renegotiation and can directly obtain Δ , the change in the monthly payment, which is a function of changes to other mortgage contract terms. For those that are not renegotiated, I have to impute $\hat{\Delta}$. I describe how I do so in Appendix Section D.²³

²²Note that when estimating these components, I will also take into account the delay between entry into serious delinquency and loan modification, and the delay in liquidating properties due to foreclosure timelines that vary across states.

²³In brief, I use a series of regressions and their predicted values to impute the change in interest rate, balance, principal forbearance and remaining term that would have been given to those loans that were not modified.

3 Empirical Frameworks

In the previous section, a simple conceptual framework shows that the estimation of the gains hinges on estimating a model of the effect of debt renegotiation on the number of monthly payments completed following 90+ days delinquency. It is crucial to use the appropriate empirical frameworks to model these effects. Otherwise the estimates of $T_{i,Mod}$ and $T_{i,NoMod}$ will be biased as they will not fully account for the nuances of the data-generating processes in this setting.

3.1 The causal effect of renegotiation on payments completed

An important determinant of the gains from loan modifications is the expected number of monthly payments a delinquent borrower will complete depending on whether or not he receives a loan modification. To estimate the effect of renegotiation on the number of payments completed, I depart from the widely used least squares frameworks employed in the literature on mortgage renegotiation.²⁴

Let $Modify_i$ be a variable equal to 1 if loan i has been modified. $Modify_i$ is an endogenous variable and potentially correlated with characteristics of the borrower that remain unobservable to the econometrician. Failure to account for this will result in a biased estimate of the causal effect of loan modification. A second concern is the right censoring inherent in the data. This arises because I only observe the loan histories through to December 2013 and do not observe how many more payments borrowers completed beyond this date. Not accounting for this feature of the data will bias the estimate downwards. Therefore, I estimate a censored regression model of the number of payments completed following delinquency, with an endogenous dummy variable which determines whether a loan is modified or not:

$$T_i^* = Modify_i \beta + X_i' \zeta_1 + \epsilon_i \text{ where } \epsilon_i \sim N(0, \sigma_\epsilon^2) \quad (4)$$

$$T_i = \begin{cases} T_i^* & \text{if } Censored_i = 0 \\ T_i^{max} & \text{if } Censored_i = 1 \end{cases} \quad (5)$$

$$Modify_i = \mathbf{1} \{ Z_i' \gamma + X_i' \zeta_2 + v_i > 0 \} \text{ where } v_i \sim N(0, \sigma_v^2) \quad (6)$$

$$\text{and where } Cov(\epsilon_i, v_i \mid X_i) \neq 0 \neq 0$$

This is a cross-sectional setting, with one observation in the dataset for each mortgage

²⁴Earlier studies that investigated foreclosure alternatives, such as [Ambrose and Capone \(1996\)](#) imposed more structure and used simulated data. Here, I depart from the assumptions of linear frameworks but use statistical models that better resemble the data generating process.

i . X_i represents a set of borrower level characteristics that I can observe in the data.²⁵ Equations (4) and (5) lay out the censored regression framework and Equation (6) models the endogeneity of $Modify_i$. Equation (4) is the structural equation of interest. The latent variable T_i^* denotes the number of monthly payments completed by a delinquent borrower following entry into 90+ days delinquency.

The true realization of T_i^* is not always observable in the data. Let T_i be the count observed in the data. Loan histories are truncated at December 2013. If a loan i is current at this date, the data only tells me that the borrower has completed at least T_i monthly payments following entry into 90+ days delinquency. Such a loan is considered to be censored, i.e., $Censored_i = 1$.²⁶ Another loan history might have the borrower foreclosed upon before December 2013, and so he stops making additional payments. In this case, I do observe the true realization of variable T_i^* . These possibilities are reflected in Equation (5). Equations (4) and (5) together correspond to a Tobit model with right censoring, where the right censoring point T_i^{max} varies from one individual loan to the other.

Equation (6) describes a probit model of the decision to renegotiate a seriously delinquent mortgage. The decision is based on based on X_i , a variable or vector Z_i that is excluded from the structural equation (4), and a normally distributed shock v_i . Importantly, the variation in Z_i is assumed to affect the decision to renegotiate the loan, but not the decision of the borrower to make monthly payments following delinquency. The endogeneity problem arises through the assumption $Cov(\epsilon_i, v_i | X_i) \neq 0$. This reflects the possibility that unobserved factors driving the decision to modify that are correlated with borrower outcome T_i^* may not be captured by the covariates X_i , thus resulting in biased estimates of β .

In order for the estimate of coefficient β to be free of endogeneity bias, Z_i must satisfy two assumptions. First, $Cov(Z_i, Modify_i | X_i) \neq 0$ and second, $Cov(Z_i, \epsilon_i | X_i) = 0$. The first states that conditional on observable X_i , Z_i affects whether the loan gets renegotiated. The

²⁵The following are included as control variables in all regressions: For the following variables, a spline with knots at each quintile: loan to value ratio, loan amount, credit score, original interest rate, house price change over the 12 month period prior to entry into serious delinquency. I also include dummy variables for the purpose of the loan (cash out refinance, rate refinance, purchase, or unknown); whether it is private label or GSE securitized; whether information on debt to income ratio is missing. I also include the debt to income ratio as a control if it is not missing. Finally, CBSA fixed effects, time of delinquency fixed effects, and originator by agency (PLS or GSE) fixed effects will be included.

²⁶Note here that the definition of censoring differs from that of the classical mortgage setting. For example, consider a hazard model of loan default. Here, a loan's time series observations would be considered censored if the loan terminates due to prepayment, or leaves the sample for other reasons, such as the transferring of Servicing rights. In the case of this hazard model, the latent variable which measures time to default will not be observed by the econometrician if the loan leaves the sample for these alternative assumptions. However, similar to the setting of the hazard rate of default, T_i^* will be assumed to be censored if I do not observe the loan history due to the fact that I stop observing loan histories in December 2013.

second assumption states that the only way the variation in Z_i can affect the borrower's decision to make monthly payments is through its effect on the decision to renegotiate the loan. The variables that satisfy these restrictions are discussed in Section 3.2. Having found such a Z_i , the system of equations can be estimated using maximum likelihood.²⁷

I use the parameters of the model to form estimates of $T_{i,Mod}$ and $T_{i,NoMod}$ at the loan level²⁸:

$$\widehat{T_{i,Mod}} = E [T_i^* | T_i^* > 0, X_i, Modify_i = 1] \quad (7)$$

$$\widehat{T_{i,NoMod}} = E [T_i^* | T_i^* > 0, X_i, Modify_i = 0] \quad (8)$$

3.2 Instrumental variables approach

The validity of the analysis described above hinges on the appropriate choice of variables Z_i . Without these instrumental variables, any estimate of the gains from modification will be biased. This section discusses the strategy used to overcome this concern. In general, I will be estimating regressions of the type:

$$Y_i = Modify_i \beta + X_i' \zeta + \epsilon_i \quad (9)$$

where i denotes each individual loan. Y_i denotes the outcome variable of interest and X_i represents loan, borrower, and geography related control variables. Note that I have suppressed time related subscripts in the above equation. To identify β using Ordinary Least Squares, the assumption $Cov(Modify_i, \epsilon_i | X_i) = 0$ needs to be satisfied. That is, conditional on loan and borrower characteristics, loan modification should be as good as randomly assigned. Satisfaction of this assumption appears unlikely given that the servicers have a larger information set than I do and will select borrowers into loan modification based on characteristics that are unobservable to me. To correctly identify β , I need to isolate variation in the probability that a loan gets modified which is uncorrelated with shocks to the borrower, ϵ_i .

²⁷Appendix G derives the log-likelihood function for both the censored regression model, and the censored regression with endogenous dummy variable model. The discussion in Wooldridge (2010) demonstrates why a simple two step estimator using predicted values of $Modify_i$ from a first step linear probability model cannot be used as it is an endogenous dummy variable. Hence, one has to estimate the system using full information maximum likelihood.

²⁸Note that T_{NoMod} will be adjusted to take into account the time lag between entry into serious delinquency and completion of the loan modification.

In Section 2.1, I describe the unique feature of the mortgage market in that loans are monitored not by the investors but by a third party—the mortgage servicer—who has discretion over the decision to renegotiate or not. In Figure 1 I document variation across servicers in my sample in their propensity to modify a loan that has become 90+ days delinquent. In particular, I run the regression:

$$Y_{ict_0(i)} = \alpha + \sum_{s \in S} \sum_t \beta_{0,s,t} \mathbf{1}_{\text{Servicer}=s \text{ and } t_0(i)=t} + X'_i \beta_1 + \gamma_{ct_0(i)} + \epsilon_{ict_0(i)} \quad (10)$$

where Y_i is an indicator variable for whether loan i , that went delinquent at time $t_0(i)$ gets renegotiated; $\mathbf{1}_{\text{Servicer}=s \text{ and } t_0(i)=t}$ is an indicator variable for whether the loan was monitored by servicer s and went delinquent for the first time at $t_0(i)$; and $\gamma_{ct_0(i)}$ are CBSA by time of serious delinquency fixed effects. Figure 1 plots the $\beta_{0,s,t}$ coefficients from this regression, with each line corresponding to a given servicer s .²⁹ I also observe variation across servicers in the hazard rate to loan modification. To document this variation I estimate a proportional hazards model of entry into loan modification conditional on being seriously delinquent. I allow for servicer specific baseline hazard functions and plot them in Figure 2.

These figures highlight that substantial heterogeneity exists in servicer behaviour even after controlling for a comprehensive set of covariates. The variation is not driven purely by the mix of borrowers serviced by each intermediary. The partial F-statistic of the joint test of significance of all fixed effects in Figure 1 equals 145, showing that they are important predictors of the propensity to modify a loan.

The literature suggests that agency problems, the mechanisms and contracts to alleviate them, and other important institutional features of mortgage securitization lead to such variation across servicers. In a theoretical model Mooradian and Pichler (2013) show that the optimal contract which overcomes asymmetric information and aligns the servicer’s and investors’ incentives will influence the rate of loan modification. Parties within the securitization chain may be affiliated with each other based on decisions about which securitization an originator sells his mortgage pools into, or depending on who retains the servicing rights.³⁰ Agarwal et al. (2014) show that affiliation between the owner of a borrower’s sec-

²⁹The omitted category here are $\mathbf{1}_{\text{Servicer}=s \text{ and } t_0(i)=t}$ for which the servicer is recorded as “unknown”. Thus the coefficients can be interpreted as the propensity of each servicer to modify a loan relative to the group of loans with missing data on servicers.

³⁰For example, Wells Fargo can originate loans and then sell them into a securitization being organized by Bank of America (who is termed the deal sponsor). However, Wells Fargo may choose to retain servicing rights and continue to service this mortgage pool. Now there is an affiliation between the originator and servicer of the mortgages. Consider another example. Countrywide can be the deal sponsor of a securitization, acquire mortgage pools from a range of bank and non-bank lenders, and also purchase the servicing rights for these loans. In this case, the deal sponsor and servicer are affiliated.

ond lien mortgage and the servicer of the first lien loan can affect loss mitigation decisions (i.e. whether to foreclosure, modify, or do nothing).³¹ Huang and Nadauld (2014) provide evidence that when a servicer and the investor in the equity tranche of a mortgage backed securitization deal are the same entity, the equity tranche sees improved performance through aggressive loan modifications or a delay in foreclosing upon the borrower. Servicers take these actions to avoid recognizing losses that would first affect the equity tranche.

Both legal and economic scholarship has discussed how servicers' contracts (the pooling and servicing agreements) and their cost structure can impede renegotiation. Hunt (2009) documents substantial variation in a sample of these contracts, and argues that while most agreements do not outright ban loan modifications they may still put up obstacles to it. He comments that the heterogeneity in these contracts does leave open the possibility that servicers faced varying levels of liability risk from failure to modify in accordance with the PSA terms. Kruger (2015) studies a sample of PSAs and shows that they do affect the rate of loan modification. Servicers would have been differentially exposed to restrictive or not restrictive PSAs which would contribute to the variation documented in Figures 1 and 2. Finally Agarwal et al. (2016) show that servicers' varying operational characteristics also drive heterogeneity in propensity to renegotiate loans.

It is doubtful that these complex arrangements and institutional features of the securitization chain will be well understood by borrowers. Borrowers may have been aware of who their servicer was, but are unlikely to have known his propensity to renegotiate, and how his practices differed from other servicers.³² This is precisely the variation that will be used in the application of the instrumental variables approach. I argue that the exclusion restriction, $Cov(Z_i, \epsilon_i \mid X_i) = 0$, will be satisfied as variation across servicers Z_i , conditional on observable X_i , will be exogenous to borrowers' decisions on the number of payments to complete—it will be uncorrelated with ϵ_i . In other words the servicer's propensity to modify, Z_i , can affect the outcome variable Y_i only through its effect on whether a particular mortgage is renegotiated. This likely holds true for other dependent variables one can consider, such as consumption of the borrower. I use the identity of the mortgage servicer interacted with the timing of the delinquency as instrumental variables for whether a loan receives a modification. In other words, let $\Lambda_{S_i \times t_0(i)}$ denote the servicer by time of delinquency fixed

³¹My results are robust to controlling for whether the property had a second lien on it or not. This should account for the effect of the second lien on decisions to make payments and consume. However, as I will shortly discuss, I assume that the ownership of this second lien, and whether the owner is affiliated with the servicer are exogenous to these outcome variables.

³²Moreover, given that the longer the borrower stays in delinquency, the larger the negative effect on their credit score, it would have been costly for borrowers to learn this propensity by remaining delinquent without trying to recover.

effects and let $Z_i = \Lambda_{S_i \times t_0(i)}$.³³

One challenge to the exclusion restriction arises from the possibility of endogenous sorting or matching of borrowers and servicers on dimensions that will not be captured by covariates. However servicers are assigned to loans just before closing of residential mortgage backed securitization deals and the borrower does not have the ability to choose who his mortgage servicer is.³⁴

While the exclusion restriction can never explicitly be tested, I provide some reassurance about its satisfaction with a test carried out in Section 7.1. In particular, I use the sample of all originated mortgages and show that controlling flexibly for observable covariates, there is little remaining variation across servicers' portfolios in the probability that a loan becomes 90+ days delinquent.

4 Data

In order to perform the tests outlined in the previous section, I require mortgage data that satisfies a few key requirements. First, I need to construct T_i , a measure of the number of payments completed by borrowers after they become seriously delinquent. To do so requires, for every borrower, monthly data on whether or not they make their mortgage payment on time. Second, I need to know the identity of the mortgage servicer to construct the instrument Z_i . Third, the data should include details on when the modification was completed, and how the mortgage contract changed as a result. Finally, the data should provide me with a rich set of covariates to control for observable differences between borrowers in my sample.³⁵

I use three datasets which satisfy the above requirements to estimate the causal effect of loan modification on the number of payments made by borrowers. The first dataset is the ABSNet Loan database, which covers over 90% of the loans that provided collateral for private label residential mortgage backed securitizations. This data is compiled using detailed reports from the securitization trustees. They include information about the borrower and the mortgage contract at origination, identify loans that were modified, and describe how they

³³Note that when I estimate the effect of loan modification on borrowers, I will be in a panel rather than cross-sectional setting. Thus, I will use $Z_{it} = \Lambda_{S_i \times (t-t_0(i))}$ i.e. servicer by time since delinquency fixed effects. Intuitively, this is using the variation that has been documented in Figure 2.

³⁴One can contrast this setting with that of corporate debt, where a firm may choose whether to borrow from public markets or from a bank based on the fact that each channel possesses different monitoring and renegotiation technologies. For example, see Rajan (1992).

³⁵Additionally, data on borrower-level consumption will be required to confirm the hypotheses that borrowers stand to gain substantially from loan modifications.

were modified. Moreover, they also include a count, for every month that the loan remains active, of the number of payments missed by the borrower. Finally, the dataset includes the name of the mortgage servicer.

The second and third datasets are the publicly available data on Fannie Mae and Freddie Mac 30 Year Fixed Rate mortgages. These agencies publish data on a subset of the mortgages that reside in their securitizations. Like the ABSNet Loan data, it includes detailed information about the borrowers and contracts at origination, and provides me with a count of the number of payments completed by the borrower while also identifying the mortgage servicer. While these data identify when a loan is modified, the change in the contract has to be inferred from the monthly performance data.

Mortgage contracts are complicated objects and come in various forms, from the standard 30 Year Fixed Rate Mortgage to more complex products such as adjustable-rate or interest-only mortgages. The parsimony of my framework points me to focus on the 30 Year Fixed Rate mortgage, the simplest of these contracts with a more straightforward repayment structure. This is the primary restriction I apply in order to minimize the distance between assumptions made in the framework above and the actual nature of cash flows to investors. A discussion of these, and additional, data restrictions appears in Appendix Section C.

One of the key dependent variables will be the number of payments completed by the borrower following his entry into serious delinquency, i.e., T_i . In order to construct this variable I use the ABSNet Loan, Fannie Mae and Freddie Mac data. This measure is created by keeping a count of the number of payments missed, and subtracting this from the number of months since serious delinquency. Other variables in the dataset are used to construct the vector of covariates, X_i .

4.1 Summary statistics

Table 1 displays summary statistics on loans that appear in the ABSNet, Fannie Mae and Freddie Mac dataset. Comparing GSE securitized and private-label mortgages, the loans look broadly similar, with privately securitized mortgages having lower credit scores and higher interest rates.

What is the change of mortgage terms implemented for an average loan modification? Figure 3 restricts attention to renegotiated loans and plots the average mortgage terms relative to a year before the loan was modified ($t = -12$ on the x axis). $t = 0$ corresponds to the quarter in which the loan is modified. The overall effect of the loan modification can be seen in the top left graph; the renegotiation reduces monthly mortgage payments by \$400, on average. This

is brought about by changing the three main mortgage terms—interest rate, outstanding balance, and maturity. Interest rates decrease by about 250 basis points following loan modification; outstanding balance increases by about \$6000; and the maturity of the loan is extended by 30 months. Note that the loan modification may involve a principal forbearance wherein a portion of the principal balance will be converted to interest free debt.³⁶ About 15% of loan modifications involve principal forbearance.

In general, these data suggest that investors trade off increases in principal balances, decreases in interest rates and increases in the mortgage maturity in order to reduce the monthly payment.

5 Results: Estimating gains to investors

With the main elements of the methodology now established, this section presents the results of the paper. As outlined above, the gains to investors can be characterised by combining an estimate of the additional cash flows that result from loan modification with assumptions about discount rates and house prices.

5.1 Estimating the effect on payments completed following delinquency

The first model I estimate is that of the causal effect of loan modification on the number of monthly payments completed by the borrower following entry into serious delinquency. To build intuition, consider Figure 4 which shows the empirical cumulative density function of T_i for two separate groups of delinquent loans—those that were and were not renegotiated. The figure shows that if you are a delinquent borrower who does not receive a loan modification, there is a 10% probability that you make greater than 20 additional monthly payments. However, if you did receive a loan modification, this probability increases to 60%. This pattern is also reflected in the averages shown on Table 1.

As described earlier, a naive comparison of these averages will not identify the effect of loan modification. First, such a comparison will not take into account the endogenous selection into receiving a modification. Second, since I only observe loan performance until December

³⁶While these loan modifications are not directly identified in the data, I can use the mortgage formulas for the computation of the monthly payments to impute the amount of forbearance. The balance of the mortgage might also increase after modification due to the capitalization of missed payments into the outstanding balance of the mortgage.

2013, a comparison of the averages will not account for the payments that are completed after this date.

To tackle this problem, I estimate the model specified in Equations (4) to (6), which accounts for both the endogeneity and the right-censoring. To better understand the effects of each of these elements of the data-generating process, I estimate a range of specifications. The results appear in Table 2. Column 1 presents the results from a simple OLS regression of T_i on an indicator variable for whether the loan was modified, loan level covariates, CBSA fixed effects, time of delinquency fixed effects and originator by agency fixed effects.³⁷ This specification ignores both the endogeneity of treatment and the right-censoring - hence I refer to it as the naive estimate. The OLS estimate suggests that modification will result in 19 additional monthly payments made by the borrower. In Column 2 I repeat this analysis with CBSA by Time of Delinquency fixed effects, and demonstrate that the result in Column 1 is not biased by time varying CBSA level unobserved heterogeneity.

In Column 3, I present results from a censored regression framework, which accounts for the right censoring in the dependent variable but not for the endogenous selection into loan modification. The coefficient on $Modify_i$ is 35, however the appropriate statistic to compare to the estimate in Column 1 is the average partial effect, which here will be 27. In other words, this specification tells us that loan modification will increase the number of payments completed by 27. As expected, the right censoring has biased my naive estimate downwards.

In Column 4, I move back to a least-squares linear regression specification which ignores the right-censoring but now accounts for the endogenous selection into treatment. This specification implies that loan modifications lead to 38 additional monthly payments from the borrower. Failure to account for endogenous selection biases the naive estimate (Column 1) downwards. In other words, the selection bias is negative and the counterfactual expected number of payments completed by borrowers who received a loan modification will be lower than the expected payments completed by those who did not. The direction of the bias suggests that servicers chose to modify loans of those borrowers who would really have struggled to complete additional monthly payments without a renegotiation. There is suggestive evidence of this in the data, with selection into modification on observables such as credit score being negative. If the bias went the other way, it would indicate that they renegotiated mortgages which were more likely to have self-cured in the absence of a modification. In Column 5, I repeat the analysis with CBSA by time of delinquency fixed effects, and show that it is robust to controlling for all CBSA level time-varying heterogeneity.

³⁷Here agency simply refers to whether the loan was in a Fannie Mae/Freddie Mac securitization, or whether it was in a private-label securitization.

Finally, in Column 6, I estimate the model which accounts for both the endogeneity in the decision to renegotiate, and the right censoring in the data-generating process. The β coefficient in Equation (4) is estimated to be 73.7. The resulting average partial effect reflects that, on average, renegotiation of the mortgage leads to 56 additional monthly payments from borrowers who become 90+ days delinquent. Note that the censoring framework takes into account that although a large number of borrowers re-default following entry into serious delinquency, there still are those who continue to make a large number of monthly payments. The nature of loan-level mortgage data precludes the observation of these additional payments which they would complete. It is crucial to correctly quantify these payments as they represent monthly cash flows to investors for interest and amortization of principal.

Next using (7) and (8), I construct estimates of $\widehat{T_{i,Mod}}$ and $\widehat{T_{i,NoMod}}$, the expected number of payments completed by a delinquent borrower with and without renegotiation, respectively. Figure 5 below plots the densities of these constructed measures. On average, the difference between the means will be approximately 60 monthly payments, which is close to the Average Partial Effect estimated above. These estimates allow me to compute the gains to investors from renegotiation.

5.2 Imputing loan modifications for non-modified loans

In order to estimate the gains from loan modification, I need to construct, for loans that did not get renegotiated, an estimate of the counterfactual change in monthly payment as if they had been renegotiated. In order to do so, I follow the procedure outlined in Appendix Section D. Essentially, I estimate a series of regressions on loans with $Modify_i = 1$, and having estimated the parameters of these specifications, use predicted values from them to impute the counterfactual change in interest rate, outstanding balance, remaining term, and principal forbearance for those loans with $Modify_i = 0$. In Table 3, I report summary statistics on the distribution of $\frac{d+\Delta}{d}$, the ratio of post-modification payments to pre-modification monthly payments. The first row presents summary statistics for loans that were not modified, for which this quantity has been imputed. The second row presents summary statistics on modified loans as they appear in the data. The table demonstrates that the two distributions appear to be similar. Using these inputs, I compute $\frac{\widehat{V(\Delta)} - V(0)}{D_1}_i$, the loan level gains from loan modification to investors.

5.3 Do loan modifications result in gains to investors?

Before I use the components computed thus far to measure the gains from mortgage renegotiation, I require three additional assumptions. First, I compute house prices as at the date of delinquency, P_1 , by applying CBSA level, or state level, house price indices from the Federal Housing Finance Agency (FHFA) to the property value at origination. Second, I assume that the foreclosure discount is $\phi = 1 - 0.3 = 0.70$, following [Campbell et al. \(2011\)](#).³⁸ And finally, I assume that the annual discount rate will be based on the prevailing 30 Year Fixed Rate Mortgage rate in the FHFA's monthly Mortgage Interest Rate Survey. Figure 11, in the Appendix, shows the time series of the assumed discount rate. Given these assumptions, I am able to compute the gains to investors as depicted in Equations (2) and (3).

I form an estimate of these gains, $V(\Delta) - V(0)$, at the loan level and normalize it by the balance outstanding as at first entry into serious delinquency, D_1 . The sample mean and standard deviation of each component of the gains and of the total gains are represented as bars and vertical lines in Figure 6. In estimating the standard deviation I take into account the fact that investors observe borrower characteristics, including where they are located and when they went seriously delinquent. Therefore, I estimate the conditional standard deviation of each component of the gains.³⁹

The first component $\Delta PV(\text{Interest from PMTs})$ represents the amount that investors earn in interest as borrowers continue to make additional payments every month following mortgage renegotiation. It has a mean of 15.9% of the balance as at 90+ days delinquency and a standard deviation of 6.9%. As borrowers continue to make payments principal is amortized and gains to investors from this component ($\Delta PV(\text{Principal from PMTs})$) are represented by the second bar. This component has a mean of 7.4% of the balance as at 90+ days and a standard deviation of 2.8%. Variation across the sample in these components arises from differences in the expected number of payments completed ($T_{i,Mod}$, $T_{i,NoMod}$) and differences in the original and renegotiated terms of the mortgage.⁴⁰

The third component ($\Delta PV(\text{Termination})$) estimates the expected value to investors from the terminal cash flow from a modified loan relative to one that does not get renegotiated.

³⁸Later I present a robustness check to this assumption where I show the results assuming perfect foresight house prices. I also perform a sensitivity analysis on the assumption of ϕ , which appears in the Appendix.

³⁹I do so by estimating the regression $\hat{Y}_i = \alpha + X_i' \beta + \gamma_{ct} + \epsilon_{ict}$, where Y_i is one of the components described above. Then, I compute the standard deviation of the residuals $\hat{\epsilon}_{ict}$.

⁴⁰Appendix Figure 12 further decomposes this quantity to show that the smaller monthly payments (Δ in the framework) cost the investors about 11.4% of the balance at 90+ days, but the continuation of payments over a longer period of time helps them recover 34.7% of the balance at 90+ days.

This component too is estimated at the loan level. For example, consider a borrower who makes 56 additional monthly payments as a result of receiving a loan modification. After these 56 months the borrower may either redefault and enter foreclosure or he can prepay the outstanding balance.⁴¹ Thus loan modification extends the life of the mortgage and delays termination of the contract. The -20.7% mean of this component largely represents this time value of money cost of delaying the recovery of the outstanding balance. The principal recovered after the borrower makes these additional payments will differ from that recovered upon immediate foreclosure due to the rate at which the modified loans amortize. Appendix Figure 13 further decomposes this component to demonstrate that in absolute terms, modification and foreclosure may have been expected to recover similar portions of the outstanding loan balance, but the delay in recovery imposes substantial costs to the investor.

Overall, on average, investors expected gains from loan modification of only 2.4% of the outstanding mortgage balance at 90+ days delinquency. The unconditional standard deviation around this mean is about 19%. However, taking into account information that the investor has about the borrower, the unconditional standard deviation, the preferred estimate, is 11.8%; about 4.8 times the mean. The average balance as at 90+ days delinquency in the sample is \$202,700, implying average gains of \$4900. The estimate is smaller compared to the one based on realized losses in Maturana (2016). The difference in my estimates would arise from the fact that I consider the present value of expected gains rather than realized losses. Additionally, I adopt a different approach to estimation, and explicitly account for the right censoring in the data generating process when computing these gains.

When renegotiating a mortgage investors expose themselves to borrower-level variation as well as spatial and business-cycle variation. The standard deviations reported above represent borrower-level variation within a CBSA at a particular point of time in the business cycle. To contextualize the within borrower standard deviation of 11.8% I contrast it to across CBSA by time variation. I estimate the regression $((V(\widehat{\Delta}) - V(0))_i = \alpha + X'_i\beta + \gamma_{ct} + \epsilon_{ict})$ and plot the resulting $\widehat{\gamma}_{ct}$ in a histogram. I also plot the density of $\widehat{\epsilon}_{ict}$. The results appear in Figure 7 and show that across CBSA by Time variation is around 5.8%. Investors were exposed not only to variation in expected gains across borrowers but also to variation across geographies

The estimated mean and conditional standard deviation pertain to the expected payoff from

⁴¹Here I assume that if a borrower's LTV at the end of making these additional monthly payments is below 90% he will be able to refinance or else he will enter foreclosure. The right-censoring in the data necessitates this assumption. In the data, I observe that 30% of loans that are modified will enter foreclosure within 4 years.

a single delinquent mortgage. An investor may hold claims to multiple such delinquent loans. As N , the number of delinquent loans he holds, increases, the expected payoff will increase by a factor of N . Meanwhile, if the gains are sufficiently uncorrelated across borrowers, the standard deviation of the total payoff will increase by a factor of only \sqrt{N} . This may make loan modifications more attractive in response to delinquencies, but a few mitigating factors remain.

Note that payoffs from loan modification need not be independently distributed for borrowers in an investor's portfolio, lessening the extent to which the mean rises faster than the variance as N increases. Additionally, candidates for loan modifications were often evaluated on a case-by-case basis as the servicer collected additional information about the borrower. With few exceptions ([Mayer et al. \(2014\)](#)), it was unlikely that entire portfolios of delinquent loans would have been renegotiated. Therefore, the pertinent distribution of gains may still be that which describes the payoff to a single mortgage. Finally, while the 2.4% estimate already factors in the time over which these gains were realized, my earlier point estimate on the causal effect of loan modifications suggests that securitization conduits in need of cash may have been unlikely to wait for a period of four to five years to realize these gains. Therefore, I argue that the gains to investors were insufficient to induce mortgage renegotiation.

The results of this section complement a large literature that has documented the effect of agency problems within mortgage securitization on the rate of loan modification. This literature still leaves unanswered the question of whether investors expected substantial gains from renegotiation even in the absence of these agency problems. Using a methodology that relies on measuring how borrowers' actions change as a result of loan modification to estimate the gains to the investors allows me to provide an answer to this question. My results suggest that, on average, the expected gains from loan modification were small. Removal of agency problems may have resulted in an increase in the rate of loan modification, but only for that subset of delinquent loans from which investors expected to have positive gains.

6 Do borrowers gain from loan modifications?

From the perspective of the investors, the estimated gains do not appear to justify regulators' enthusiasm for debt renegotiation. However, reaching the appropriate policy conclusion depends crucially on whether the failure to renegotiate imposes a cost to the other side of the mortgage contract—the borrower. On one hand, indifference of borrowers to loan modifications would cast doubts on the efficiency of interventions such as HAMP. On the other, the presence of gains would imply that the failure to renegotiate leaves borrowers

worse off.

The conceptual framework developed (and described in detail in Appendix Section B) suggests that gains from modification will be reflected in the borrower’s consumption bundle. Compare, in the simple two period setting of Section 2, the borrower’s consumption bundle with modification ($W(\Delta)$) and without ($W(0)$):

$$W(\Delta) - W(0) = (-2\Delta + \theta) \quad (11)$$

The decrease in monthly payments due to the loan modifications (-2Δ) lifts constraints on borrowers and allows them to better smooth consumption. By entering a renegotiation, borrowers avoid the costs of entering foreclosure, which may include legal expenses, relocation costs, and loss of access to credit markets, among others. However, entering foreclosure would have resulted in a period of free rent, or relocation to housing with a lower user cost. The net effect of avoiding foreclosure is thus captured by θ , which may be positive or negative.⁴²

Following Di Maggio et al. (2014), I use microdata from a credit registry to construct borrower level proxies for durable consumption and facilitate a test for the effect of renegotiation on borrowers. This proxy infers the frequency and the size of automobile purchases made by borrowers from data on their automobile loans (see Appendix Section E for details on the data source and the construction of the variables). Studying a consumption proxy as the outcome variable allows me to summarize the effect of loan modification on various parts of the borrower’s budget constraint. However, it ignores gains that depend on the borrower’s intertemporal preferences or risk-aversion. I also study the effect on borrowers’ credit scores, and on large discrete increases in balances of unsecured non-mortgage credit as a proxy to credit-card spending.

First, I use a within-borrower OLS event study methodology to test for the effect of loan modification on consumption. This approach uses only the sample of borrowers who received loan modifications and exploits variation in the timing of the mortgage modification. The results of these regressions appear in Figure 9. However, this does not constitute a causal estimate and so I turn to the instrumental variables (IV) approach. The IV approach is an adaptation of the difference-in-differences estimator, wherein I now use as a control group those borrowers who did not receive loan modifications, but were equally deep into their delinquency as those who did. Assignment to treatment is effectively randomized by using

⁴²As Appendix Section B makes clear, I assume that the borrower does not change their housing consumption following foreclosure. Thus, implicit here is the assumption that if a borrower loses a home through foreclosure they will continue to consume housing and pay rent, which in this case is equal to d per period. θ will also capture any deviations from this assumption.

the instrumental variables described in Section 3.2. The results of this approach appear in Table 4. A detailed discussion of the estimating equations appears in Appendix Section F.

The sharp response of durable purchases documented in Figure 9 points to a substantial relaxation of a delinquent borrower’s liquidity constraint following loan modification. That borrowers who do receive loan modifications have very similar pre-modification consumption to those who do not receive loan modifications further reinforces this finding (see Appendix Figure 14, which compares borrowers with and without loan modifications).⁴³ The effect on consumption is confirmed by the instrumental variables analysis in Column 5 of the panels in Table 4. Borrowers increase consumption by \$66 to \$115 per month depending on the specification considered. In present value terms this will amount to \$5,750 which amounts to 2.8% of the borrower’s outstanding balance as at entry into 90+ days delinquency.⁴⁴ Moreover, for every dollar decrease in the monthly payment resulting from the loan modification, borrowers will consume about 20 to 32 cents suggesting an elasticity that can be compared favourable to those from other contexts in the mortgage market (Di Maggio et al. (2014), Keys et al. (2014), Agarwal et al. (2015)). The increase in consumption may be facilitated by regained access to credit markets as borrowers see a marked increase in their credit scores over time.

The interpretation that these results represent gains to borrowers may be thrown into question by the possibility that borrowers who consume more are also more likely to redefault. However, there is weak or no correlation between post-modification purchase of an automobile and subsequent re-entry into delinquency, as shown in Appendix Table 8.

Such gains to the borrower are foregone for the average loan that does not get renegotiated. They are particularly salient for borrowers with serious delinquencies who did not have access to debt relief programs such as Home Affordable Refinancing Program, and did not reap the benefits of the Federal Reserve’s quantitative easing (Fuster and Willen (2010) and Di Maggio et al. (2016)). Therefore, a planner with the objective of increasing borrower welfare may want to intervene and encourage loan modifications. However, in doing so he must target the participation constraint of investors.

⁴³A large literature has tested for the effects on consumption of shocks to the borrower. See Agarwal and Qian (2014), Jappelli and Pistaferri (2010), Parker et al. (2013) for some recent examples outside the context of mortgage markets. The high elasticity of 32 cents per dollar is consistent with these borrowers being more liquidity constrained than those in other studies Zeldes (1989).

⁴⁴Assuming an annual discount rate of 4.9%. I find this discount rate by finding, for each delinquent loan, the average FHFA MIRs rate at the time of first entry into serious delinquency, and then taking an average over the sample.

7 Robustness checks and extensions

Having concluded the main analysis, this section describes a few extensions of the results and presents some robustness checks.

7.1 Investigating the exclusion restriction

In order to successfully apply the instrumental variables approach (described in Section 3.2), the exclusion restriction must hold true. The exclusion restriction asserts that the servicer’s loan modification strategies affect borrower level outcomes only through their effect on whether the loan gets modified. In other words, it asserts that there is no correlation between servicer fixed effects (the instrument) and unobservable variation in borrower level outcomes. While the exclusion restriction cannot be directly tested, in this section I propose a test which can at least reassure me of its satisfaction. The test revolves around the idea that although my analysis has been performed on loans that become 90+ days delinquent I still have in my dataset 30 Year Fixed Rate Mortgages that did not become seriously delinquent. Hence, I can test for whether there are differences between the portfolios of various servicers in the probability that their loans are becoming seriously delinquent.

A quick glance at the characteristics of the portfolios of the servicers in my sample demonstrates that we might expect them to perform differently. After all, some of them specialized in subprime segments of the market (e.g. Ocwen, Countrywide), while others serviced mostly prime loans (e.g. J.P. Morgan Chase). These observable differences among servicers do not pose a challenge to identification because they can be controlled for. The remaining concern will be that loans across servicers’ portfolios are substantially different after controlling for a rich set of observables. Studying borrowers’ entry into delinquency is one way to get a sense, at least ex-post, of the quality of the servicer’s portfolio.

This formulation of this test uses a propensity score matching method. First, I select a particular servicer, Wells Fargo for example, and estimate a probit model where the dependent variable is an indicator for whether a loan was serviced by Wells Fargo.⁴⁵ I then form propensity scores using the estimated probit model, i.e., the propensity score predicts whether a loan in another servicer’s portfolio was similar to one in Wells Fargo’s portfolio. After forming a sample of Wells Fargo loans matched to other servicers’ loans (by keeping non-Wells

⁴⁵ In the probit specification, I include as control variables a spline for loan amount, credit score, interest rate, LTV, and the change in house prices over the year prior to origination of the mortgage. I also include an indicator variable for whether the loan was a private label securitized loan, indicator variables for various loan purposes, CBSA fixed effects, and origination date fixed effects.

Fargo loans with propensity scores in the highest quartile of the distribution) I perform a t-test comparing the probability that a Wells Fargo loan entered serious delinquency within 36 months of origination to the probability that a loan from the matched sample entered serious delinquency within 36 months of origination. Standard errors are clustered at the state level. I then repeat this for each of the top 15 servicers in the sample. I report the results of each t-test and the associated 95% confidence intervals in Figure 8.

I divide this figure into two panels; the panel on the left shows the servicers who satisfy this robustness check while the one on the right shows those who don't. On the x axis I show the market share of a given servicer. As can be seen, those servicers that do have portfolios that look different from their competitors only hold a small portion of the market share. All my results go through once I drop these servicers. On the left hand side panel I also plot the average rate of entry into 90+ days delinquency in the sample of 14%, highlighting that even if these servicers' portfolios are statistically different from their competitors, the size of this difference appears economically insignificant.

7.2 Can certain modification types help investors and borrowers?

The results of the preceding sections suggest a scope for intervention to encourage investors to engage in loan modifications and unlock gains to borrowers. Regulatory agencies often encouraged the use of principal reduction, i.e., an immediate write-off of a portion of the debt. However, my results suggest that, in fact, binding liquidity constraints sent borrowers into delinquency. [Ganong and Noel \(2017\)](#) also describe how borrowers were more sensitive to binding, short-term, liquidity constraints rendering principal reductions ineffective in response to widespread delinquencies. In such a setting, [Eberly and Krishnamurthy \(2014\)](#) show that the optimal loan modification would take the form of principal forbearance. Principal forbearance may be preferred by investors as it avoids the immediate principal write-off and allows a further relaxation of a borrower's constraint by back-loading repayment of the debt.

Indeed, as Figure 10 shows borrowers do appear to benefit from principal forbearance. Controlling for a change in the outstanding balance, a larger decrease in the monthly payment is correlated with a stronger consumption response. Surprisingly, controlling for changes in the monthly payment, an increase in the principal balance correlates with a larger probability of an automobile purchase.

Encouraging the right types of loan modification by combining an understanding of borrowers' constraints and the recognition of limited gains to investors may be one way a

policy-maker can encourage renegotiation in the face of wide-spread delinquency.

7.3 Heterogeneity in gains to investors

I find that gains to investors were small with a standard deviation of gains almost four times larger than the sample mean. As Table 1 shows, there is variation across mortgages on dimensions such as credit score and loan size, along with variation in the location of borrowers. To better understand what drives these gains, I estimate them across various subsets of my sample. This approach will also reveal how robust the main result is to the assumption of homogenous treatment effects assumed in Equation (4).

I divide the sample into groups based on quartiles of credit score, loan size, and change in collateral value (estimated using FHFA house price indices) between origination and first date of entry into 90+ days delinquency, and estimate the gains to investors from loan modification for each group. The results appear in Table 5. Overall, the estimate of the standard deviation of gains is similar across groups. Although, the larger the decline in house prices from origination to 90+ days delinquency (Panel B, Column 1) the lower is the variation in these gains. At the same time the average gains from modification are the largest for this group, potentially due to a lower ϕP_1 as per my framework.

These results suggest the importance of liquidation values in determining the gains from modification. Loan modifications have larger and less variant benefits for those delinquent borrowers who have experienced a large decline in house prices. This is consistent with the higher probability that such borrowers receive a loan modification.

7.4 Sensitivity to assumptions

Estimating the gains to investors involved making assumptions about some of the parameters in my model. To assess how sensitive the results are to these assumptions, I re-estimate the gains to borrowers under a series of alternative assumptions. The results appear in Table 6. Columns 1 to 4 present the mean and conditional standard deviation of the various components of the gains to loan modification. Column 5 presents across CBSA by time of delinquency variation in the gains to investors (the mean of which appears in Column 4).

I first assess the sensitivity to the assumption on ϕ , the assumed foreclosure discount. In general, the deeper the foreclosure discount (lower ϕ), the higher the gains from renegotiation. Next, I compute the gains under the assumption of perfect foresight in house prices. In my baseline result, I assume that house prices follow a random walk, i.e., there is no mean

reversion. This sensitivity analysis estimates the gains under the opposite extreme of an assumption. The results suggest that mean reversion in house prices is likely to reduce the potential gains from renegotiation, as prices may at least partially recover by the time a foreclosure auction occurs. Finally, I increased the assumed rate of mortgage redefault from 24% to 40% by changing parameters of the $G(P, D)$ function of Section 2. Intuitively, a higher rate of redefault reduces the gains from loan modification. As the results show, the changing these assumptions will affect the mean of the gains to investors in the sample. However, the conditional standard deviation of the gains always remains in the 11% to 16% range.

The estimation of expected gains is thus sensitive to the choice of key parameters. Uncertainty about these parameters would only add to the high variance of expected gains from the perspective of investors, making them less likely to favour loan modifications.

8 Conclusion

As the collapse of house prices turned into a widespread economic downturn, more and more borrowers began to become delinquent on their mortgages. To combat this debt overhang, various regulators and government agencies poured resources into renegotiation of contracts. Their efforts, however, were met with a muted response from participants in the mortgage market.

Agency problems in the securitization chain are among the main reasons proposed for this response (Agarwal et al. (2011), Piskorski et al. (2010), Korgaonkar (2016)) along with restrictive contracts faced by mortgage servicers (Levitin and Twomey (2011), Thompson (2011), Kruger (2015)). I highlight that the decision to renegotiate will depend primarily on the availability of sufficient gains from modification relative to foreclosure to both sides of the mortgage contract. Insufficient expected gains to a single party can be enough to preclude renegotiation. In this paper, I estimate and characterize these gains to investors and borrowers.

The challenge in doing so arises because loan modification is not randomly assigned to borrowers. There are observable and unobservable differences between borrowers who receive loan modifications and those who do not. A simple comparison of these two groups which fails to account for this will result in a biased estimate of the expected gains. Therefore, to identify these gains I develop an estimation framework which exploits variation in the propensity of intermediaries to modify loans. Crucially, I rely on reduced form specifications that use as dependent variables the outcome of individual borrowers' decision-making on

how many monthly payments to complete and how much and when to consume. Notably, when making these decisions, borrowers are unlikely to take into account how their servicer would be different from others.

I find that through modification of a mortgage investors expect to recover, on average, 2.4% more of the outstanding balance as at 90+ days delinquency relative to what they might expect to recover through the foreclosure process. The uncertainty about realizing these gains is highlighted by their 11.8% standard deviation. Once a loan is renegotiated, borrowers continue to make monthly payments of interest and principal and maintain mortgage amortization. However, as a result of the modification, interest rates paid by borrowers decrease by an average of 250 basis points, thus imposing a cost to investors. The loan modification extends the period of time over which principal is repaid but does not compensate investors sufficiently for doing so.

Borrowers, on the other hand, would not resist the loan modification. Renegotiation is accompanied by a sharp increase in durable consumption (measured as automobile purchases) and a slower increase in consumption using unsecured credit. Borrowers consume out of the decrease in monthly payments and do not lose access to credit markets which allows them to overcome liquidity constraints and smooth consumption.

Overall, the results suggest that servicers may have been unwilling to renegotiate loans on behalf of investors due to limited gains from renegotiation. This left borrowers significantly worse off. Hence explanations for the subdued response to government intervention need not rely solely on agency problems in mortgage securitization.

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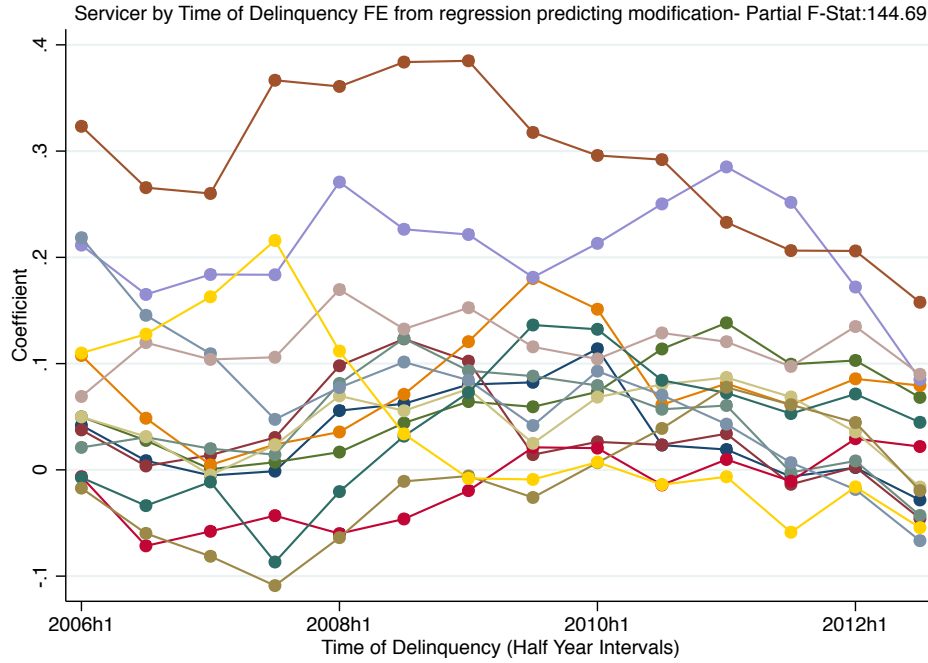


Figure 1: Servicer by Calendar Time of Delinquency Fixed Effects

The graph above displays plots, for every servicer s , the time series formed by the coefficients $\beta_{0,s,t}$ estimated from the regression $Y_{ict_0(i)} = \alpha + \sum_{s \in S} \sum_t \beta_{0,s,t} \mathbf{1}_{\text{Servicer}=s \text{ and } t_0(i)=t} + \beta_1 \cdot X_i + \gamma_c + \eta_{t_0(i)} + \epsilon_{ict_0(i)}$. The coefficients $\beta_{0,s,t}$ are those on the servicer by Time of Serious Delinquency Fixed Effects from a regression where the dependent variable is equal to 1 if loan i that became delinquent at time $t_0(i)$ is modified at any point in its subsequent loan history. The loans used in the estimation are 30 Year Fixed Rate mortgages from the ABSNet Loan Private Label Securitization Data and the Fannie Mae and Freddie Mac publicly available 30 Year Fixed Rate Mortgage data. The sample is further restricted to loans that become 90+ days delinquent at some point in their history.

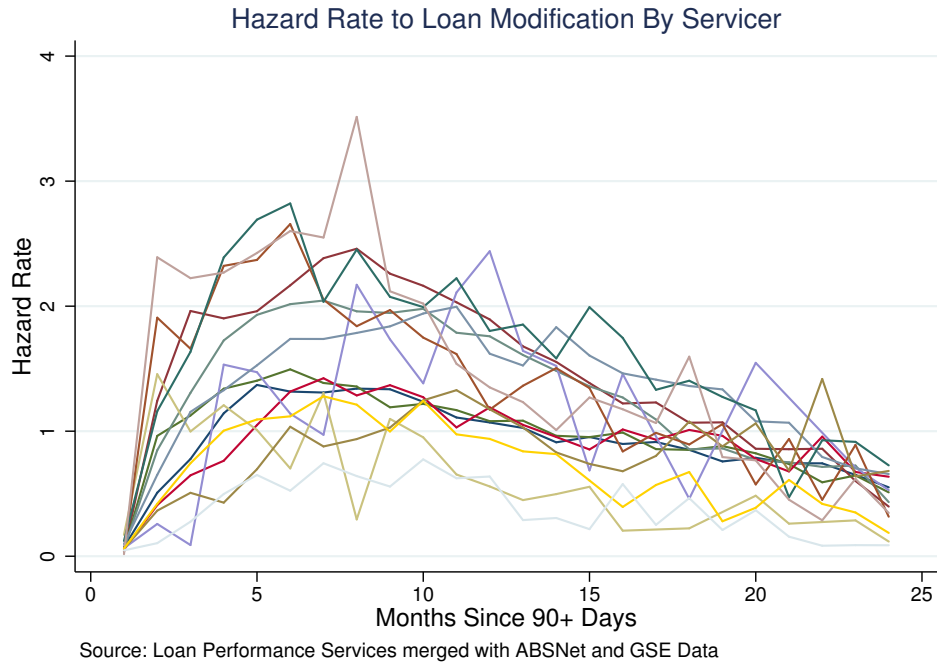
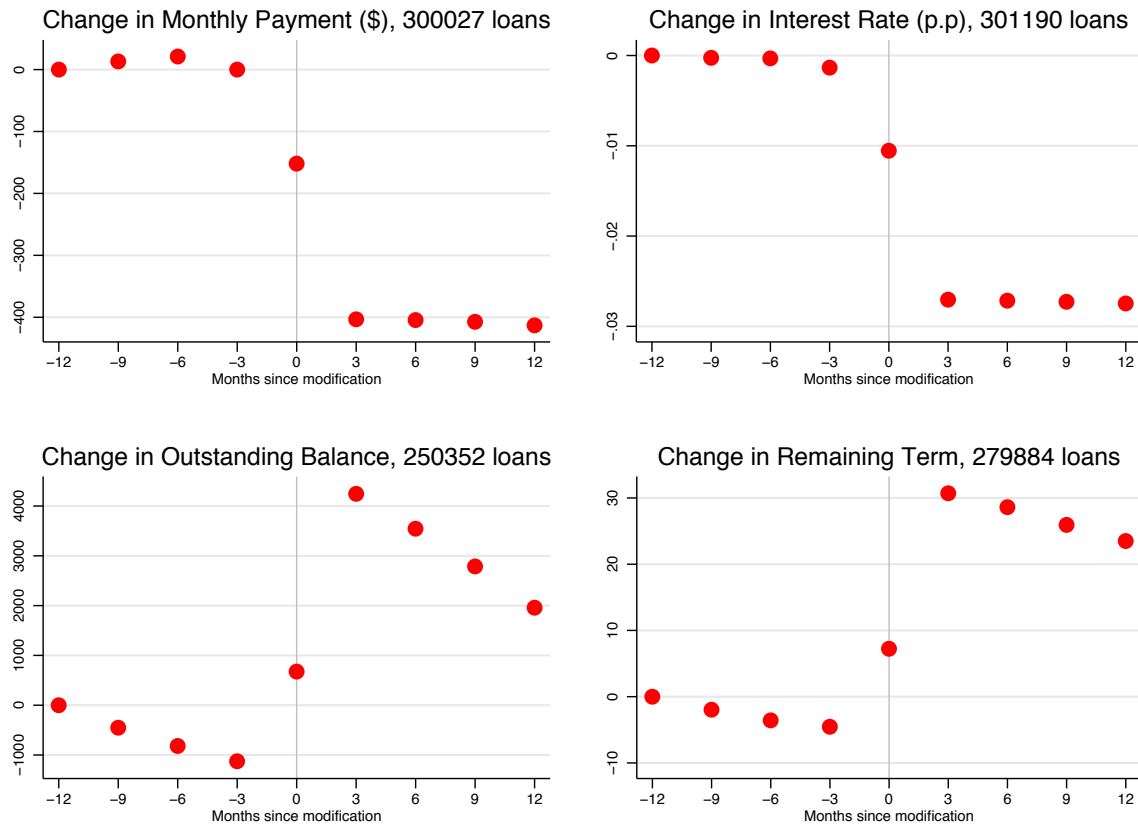


Figure 2: Servicer Specific Baseline Hazard Rate from Proportional Hazards Model of Loan Modification

The graph above displays plots, for every servicer s , the baseline hazard function from a proportional hazard model estimated using maximum likelihood. Loans enter analysis when they become 90+ days delinquent. Failure in the hazard model is specified to be the entry of a delinquent loan into a completed renegotiation. Loans that prepay, self-cure, or enter foreclosure are assumed to be censored. The loans used in the estimation are 30 Year Fixed Rate mortgages from the ABSNet Loan Private Label Securitization Data and the Fannie Mae and Freddie Mac publicly available 30 Year Fixed Rate Mortgage data that have been successfully merged with McDash Loan Performance Data so as to obtain accurate information on entry of the loan into foreclosure.



Source: McDash LPS Modified 30 Year FRMs

Figure 3: Average change in mortgage contract terms

This figure shows the change in mortgage contract terms before and after loan modification. The loans used in the estimation are 30 Year Fixed Rate mortgages from McDash Loan Performance Services Data. that become modified. Mortgage terms plotted include (clockwise from top left) monthly principal and interest payment, interest rate, outstanding principal balance and remaining mortgage term. Each plot normalizes the loan term as at 4 quarters before loan modification to 0, and plots the average loan term for 3 quarters prior to and 3 quarters after loan modification. Note that due to the aggregating of monthly performance data into quarterly intervals, the adjustment of the loan term following loan modification is not instantaneous at time 0, but the full effect manifests itself by quarter 1.

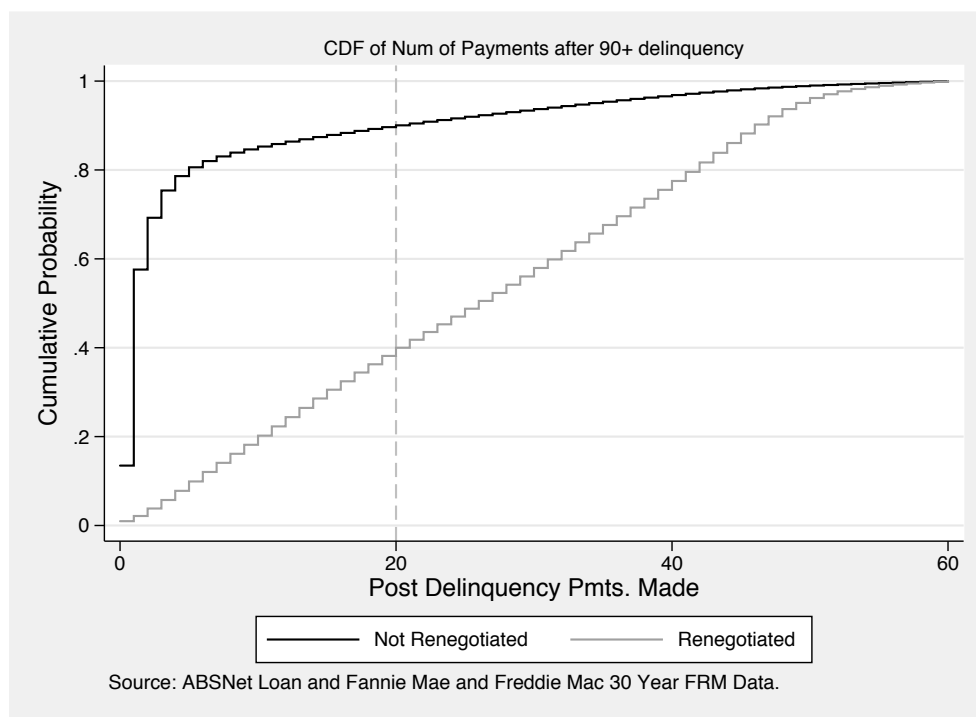


Figure 4: Empirical Cumulative Distribution Function of No. of Payments Made After Delinquency

This graph plots the empirical cumulative distribution function of the variable “Number of completed monthly payments following 90+ days delinquency”. The sample used is 30 Year Fixed Rate mortgages from the ABSNet Loan Private Label Securitization Data and the Fannie Mae and Freddie Mac publicly available 30 Year Fixed Rate Mortgage data. The sample is further restricted to loans that become at least 90+ days delinquent. The solid line plots the empirical CDF of this variable for loans that are not modified. The dashed line plots the empirical CDF of this variable for loans that are eventually modified.

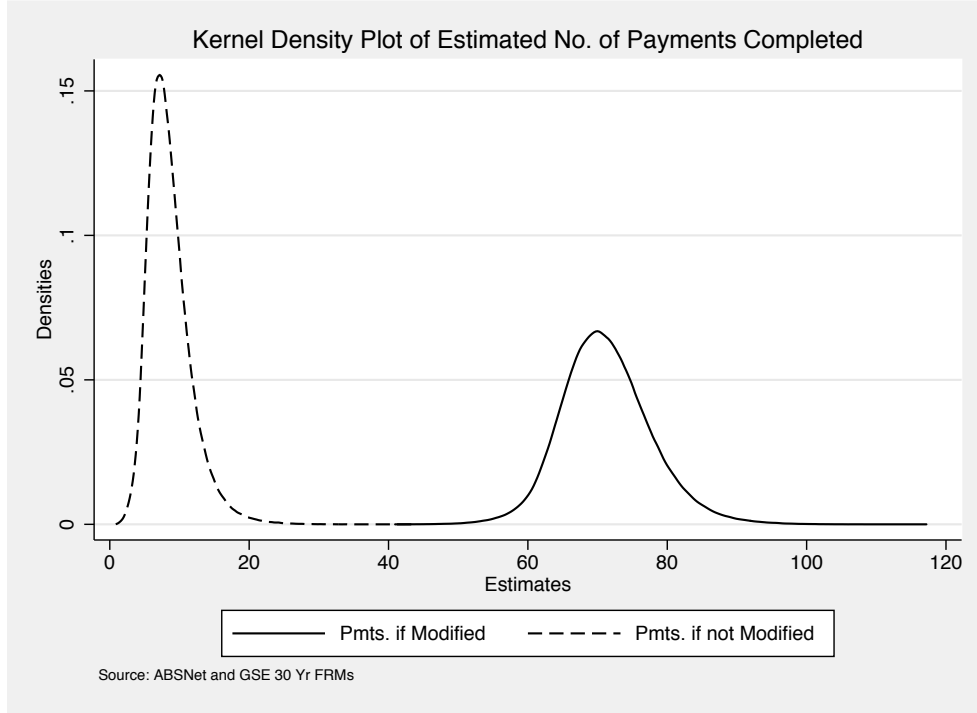


Figure 5: Distribution of $\widehat{T}_{i,Mod}$ and $\widehat{T}_{i,NoMod}$

This graph plots the empirical kernel density estimates of the predicted number of payments completed based on whether the loans would be modified or not modified. $\widehat{T}_{i,Mod}$ and $\widehat{T}_{i,NoMod}$ are the predicted values from the estimated structural equation which takes into account both the endogeneity of selection into treatment on unobservables and the right censoring inherent in the data. The sample used is 30 Year Fixed Rate mortgages from the ABSNet Loan Private Label Securitization Data and the Fannie Mae and Freddie Mac publicly available 30 Year Fixed Rate Mortgage data. The sample is further restricted to loans that became at least 90+ days delinquent. The solid line plots predicted values assuming the loans were modified. The dashed line plots predicted values for all loans assuming the loans were not modified.

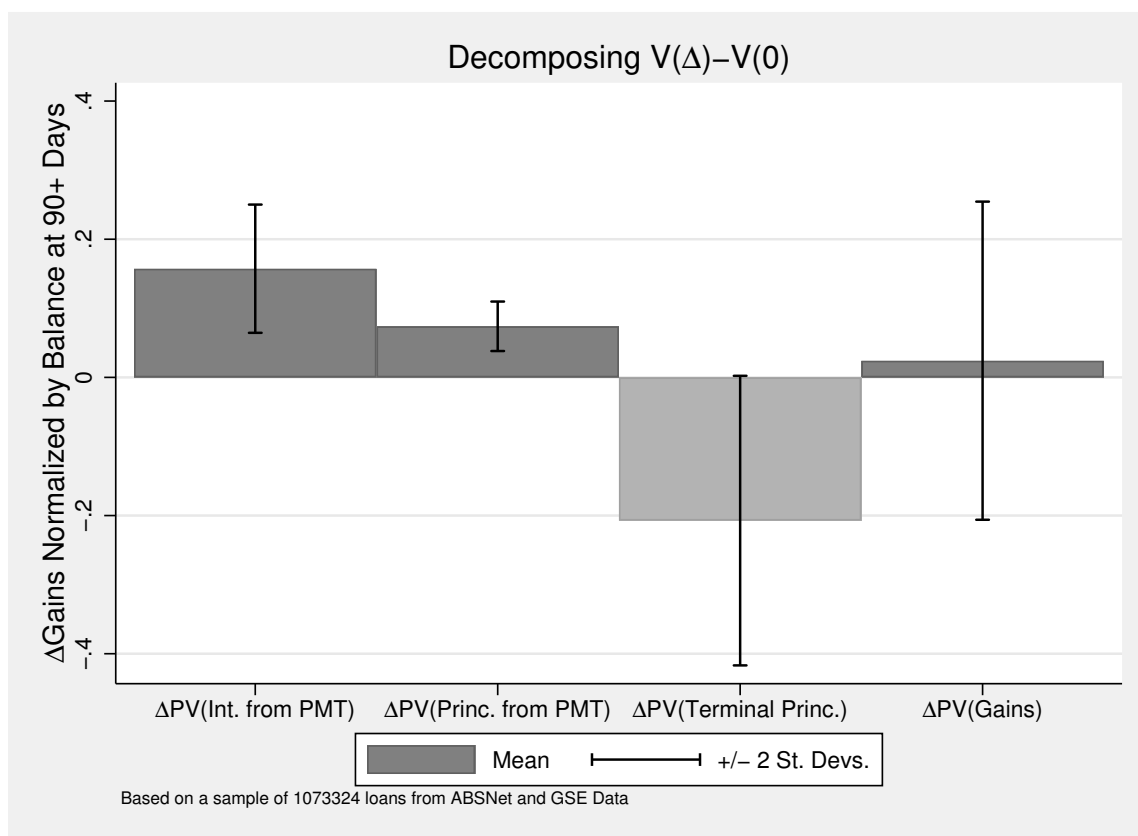
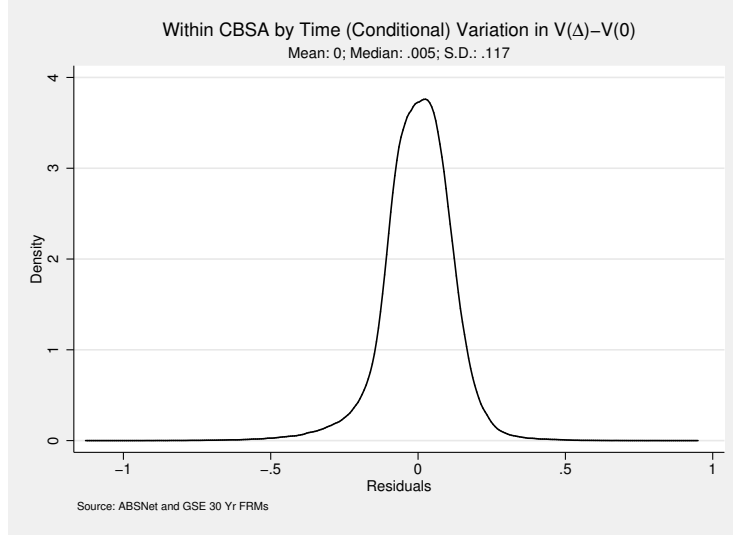


Figure 6: Decomposing the benefits from loan modification

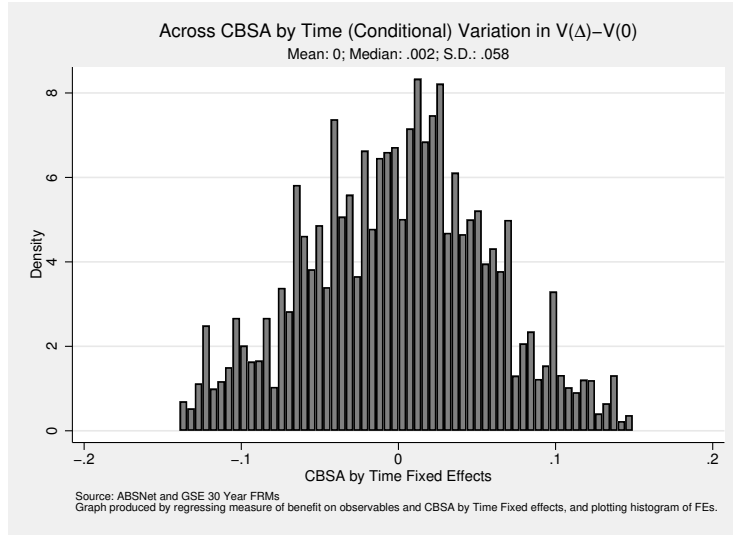
This graph shows the mean and variance of the gains from modification to investors relative to not modifying the mortgage. The bar graphs represent the means of normalized estimated gains which are measured at the loan level. The lines represent 95% confidence intervals based on the conditional standard deviation of the loan level estimates of gains from modification. The first component the present value of gains from interest earned through continued completion of monthly payments. The second component represents incremental amounts recovered of principal from continued collection of monthly payments. The third component represents the amount recovered from the termination of the mortgage after renegotiation, in present value terms, relative to the amount recovered from termination if the loan is not renegotiated. The estimates are based on my analysis on data on 30 Year Fixed Rate mortgages from ABSNet Loan, and the publicly available Fannie Mae and Freddie Mac data.

Figure 7: Within CBSA by time of delinquency variation



(a) Within CBSA by time of delinquency variation

The graph plots the density of results from a regression of my estimate of normalized gains from loan modification, i.e., I plot $\hat{\epsilon}_{ict}$ from the regression $V(\Delta) - V(0)_{ict} = \alpha + X_i' \beta + \gamma_{ct} + \epsilon_{ict}$. The estimates are based on my analysis on data on 30 Year Fixed Rate mortgages from ABSNet Loan, and the publicly available Fannie Mae and Freddie Mac data.



(b) Across CBSA by time of delinquency variation

The graph plots the density of results from a regression of my estimate of normalized gains from loan modification, i.e., I plot $\hat{\gamma}_{ct}$ from the regression $V(\Delta) - V(0)_{ict} = \alpha + X_i' \beta + \gamma_{ct} + \epsilon_{ict}$. The estimates are based on my analysis on data on 30 Year Fixed Rate mortgages from ABSNet Loan, and the publicly available Fannie Mae and Freddie Mac data.

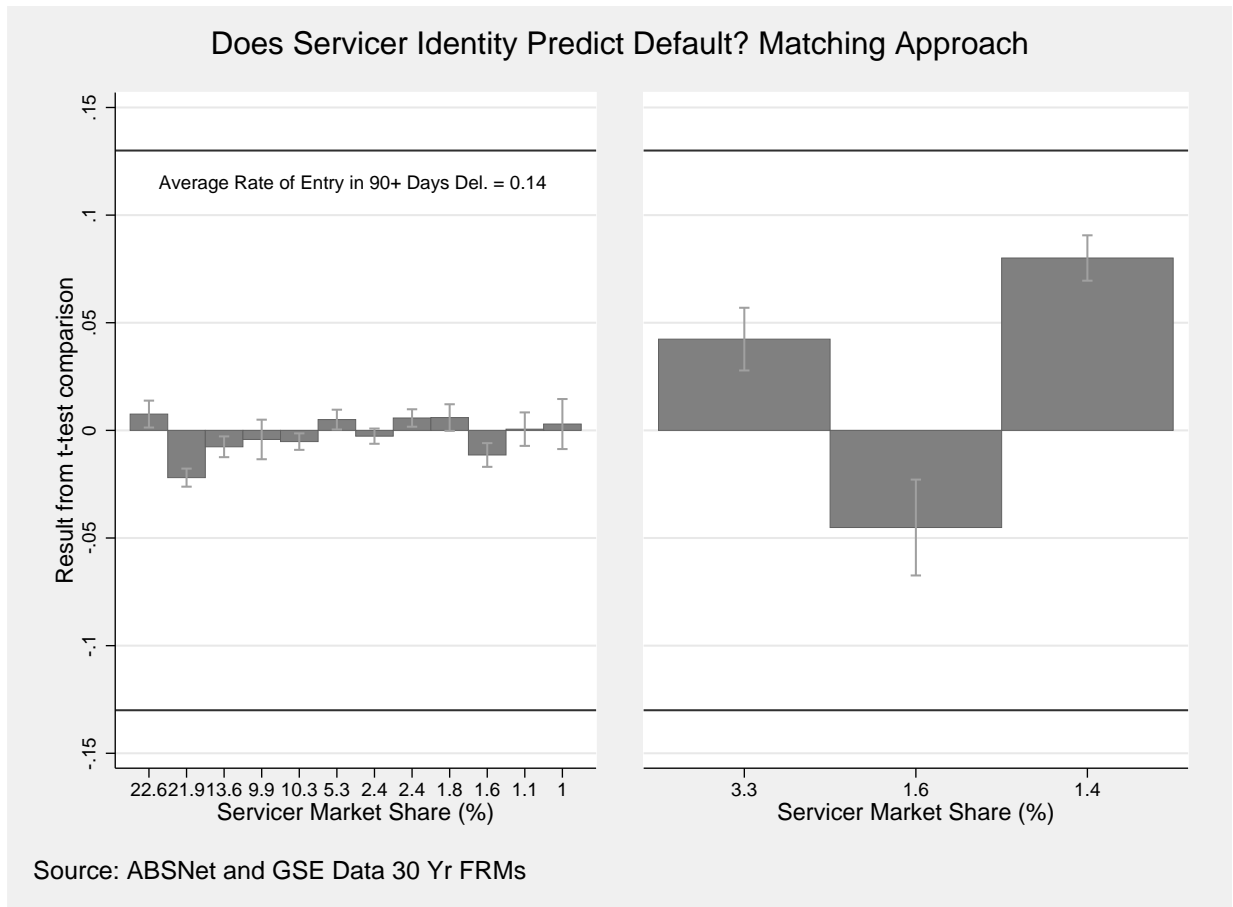
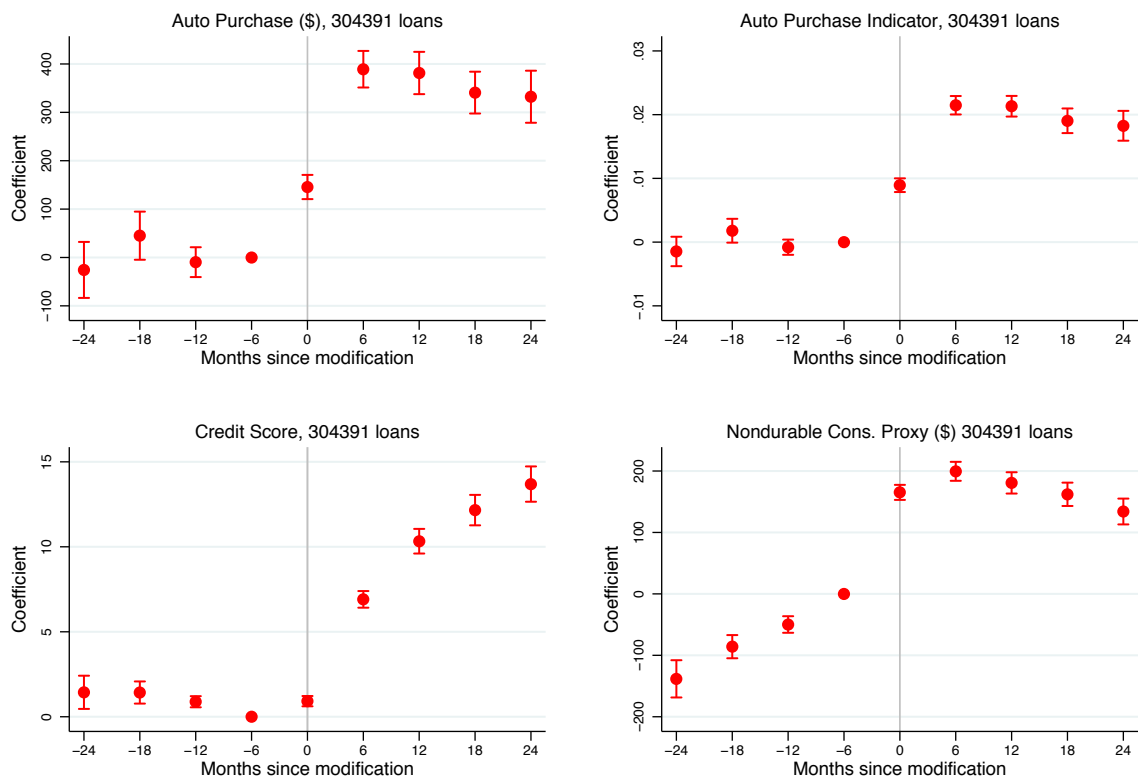


Figure 8: Assessing the exclusion restriction

This graph compares the loan performance (probability of entry into 90+ days delinquency within 36 months) for loans in the portfolios across different mortgage servicers. The y-axis shows results of a t-test comparing the loan performance of a sample of loans that belong to a servicer with market share denoted on the x-axis, with that of a matched sample (using propensity score matching) of mortgages from other servicers. The vertical lines on each bar show the clustered standard error on the difference in means from each t-test. The horizontal lines across the graphs denote the average rate of entry into 90+ days delinquency of around 14%. The panel on the left shows the set of servicers for whom I consider this robustness test to be valid. The panel on the right denotes the servicers for whom the exclusion restriction is unlikely to hold.



Source: LPS–Equifax 30 Yr FRMs.

Figure 9: Event Study of the effect of loan modification using within borrower variation

The graphs above plot results from an event study estimation of the effect of loan modification on borrower-level observables. The dependent variables used in the event studies are (clockwise from top): automobile purchases proxy variable (constructed using credit bureau data); indicator variable for whether an auto-mobile purchase was made; Equifax Vantage score (credit score) of the borrower; and the non-durable purchases proxy variable. The x-axis plots the time since loan modification in 6 month intervals, with the effect of the loan modification in the 6 month interval before modification ($t = -1$) normalized to 0. The loans used in the estimation are 30 Year Fixed Rate mortgages from McDash Loan Performance Services Data that have been modified. Standard errors are clustered at the county level.

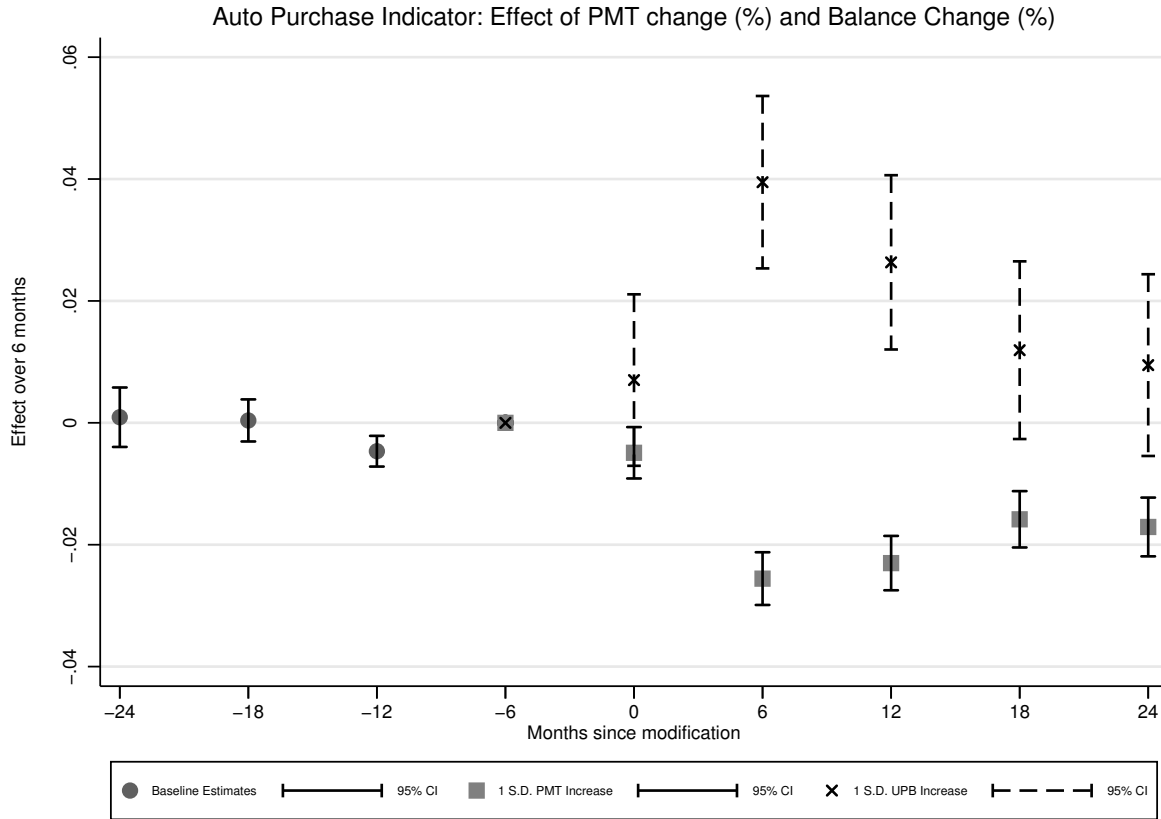


Figure 10: Heterogeneity in loan modifications and consumption

The graph above plots estimates from an OLS event study regression. The sample of loans used for this analysis comes from the McDash LPS data and consists of 30 Year Fixed Rate mortgages that have been modified. The dependent variable is an indicator for whether or not an automobile purchase took place within a given 6 month time period. I control for borrower level fixed effects, indicator variable for 6 month period before each loan was modified (coefficient plotted as a circle), indicator variables for every 6 month period after a loan was modified interacted with a standardized measure of the relative change in mortgage monthly payments (coefficient plotted as a cross) and indicator variables for every 6 month period after a loan was modified interacted with a standardized measure of the relative change in mortgage outstanding balance (coefficient plotted as a square). I also control for county by time fixed effects, time since delinquency fixed effects and

Table 1: Summary Statistics for 90+ Days Delinquent Mortgages (Fannie Mae, Freddie Mac, ABSNet)

The table below displays summary statistics on mortgages that enter the analysis. The loans used to construct the summary statistics are 30 Year Fixed Rate mortgages from the ABSNet Loan Private Label Securitization Data and the Fannie Mae and Freddie Mac publicly available data. The sample is restricted to those loans that become at least 90+ days delinquent at some point in their history. The table displays summary statistics as at the origination of the mortgage, or summary statistics on the type of loan modification obtained.

	Fannie Mae - Freddie Mac			ABSNet Loan		
	GSE Loans			Private Label Securitized		
	N	Mean	SD	N	Mean	SD
FICO \geq 680 (%)	781296	0.50	0.50	559970	0.36	0.48
620 \leq FICO $<$ 680 (%)	781296	0.39	0.49	559970	0.37	0.48
FICO $<$ 620 (%)	781296	0.11	0.32	559970	0.27	0.44
Origination LTV	783687	77.01	12.77	580165	78.34	14.36
Interest Rate	783693	6.25	0.47	580175	7.65	1.49
DTI	783693	39.58	12.98	580175	0.00	0.00
DTI Missing (%)	783693	0.03	0.17	580175	1.00	0.00
Purchase Loan (%)	783693	0.34	0.47	580175	0.37	0.48
Cash Out Refi (%)	783693	0.47	0.50	580175	0.49	0.50
Rate Refi (%)	783693	0.20	0.40	580175	0.13	0.34
Modified within 6 mths. of 90+ (%)	783693	0.13	0.34	580175	0.11	0.32
Modified within 12 mths. of 90+ (%)	783693	0.23	0.42	580175	0.18	0.38
Modified overall (%)	783693	0.38	0.48	580175	0.31	0.46
Principal Increase (%)	294224	0.41	0.49	178374	0.75	0.43
Rate Decrease (%)	294224	0.77	0.42	178374	0.73	0.45
Term Increase (%)	294224	0.66	0.47	178374	0.04	0.20
Payment Decrease (%)	294224	0.94	0.24	178374	0.87	0.34
<u>Number of Additional Monthly Payments After 90+ Days Delinquency</u>						
Modified Loans	294224	29.82	14.89	178374	20.49	15.03
Not Modified Loans	489469	8.16	14.88	401771	4.65	10.29

Table 2: Effect of Loan Modification on the Additional Number of Monthly Payments

The table displays estimates of the effect of loan modification on the number of additional monthly payments completed by the borrower following entry into serious delinquency. The table displays estimates from various specifications. The loans used in the estimation are 30 Year Fixed Rate mortgages from the ABSNet Loan Private Label Securitization Data and the Fannie Mae and Freddie Mac publicly available 30 Year Fixed Rate Mortgage data. The sample is further restricted to loans that become 90+ days delinquent. “Modified” is the regressor of interest in the specifications and is a variable equal to 1 if a loan is modified. The row “Modified” corresponds to parameter estimates from the various specifications. To facilitate comparison across specifications, I also compute the average partial effect as implied by the coefficient estimate from the non-linear models. Columns 1 and 2 show the estimate from an OLS regression, Column 3 shows the results from a censored regression model, Columns 4 and 5 show the results from a two-stage least squares estimation and column 6 shows the results from full maximum likelihood estimation of a censored regression model with an endogenous dummy variable.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	Cens. Reg.	IV-2SLS	IV-2SLS	IV-Cens. Reg.
VARIABLES	No. of Payments	No. of Payments	No. of Payments	No. of Payments	No. of Payments	No. of Payments
Modified	19.3236*** (0.3495)	19.2983*** (0.3523)	34.8775*** (0.3457)	37.9798*** (0.9079)	33.3944*** (1.0547)	73.7148*** (0.9299)
Average Partial Effect			26.93			55.91
Observations	1,129,593	1,129,279	1,163,585	1,129,593	1,123,368	1,129,620
R-squared	0.4122	0.4178	-	0.1467	0.2570	-
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CBSA FE	Yes	No	Yes	Yes	No	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
CBSA by Time FE	No	Yes	No	No	Yes	
Originator by Agency FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	CBSA	CBSA	CBSA	CBSA	CBSA	CBSA
Partial F-Stat	-	-	-	217	208	-

Table 3: Comparing imputed and actual change in monthly payments

The table present summary statistics on the distribution of $\frac{d+\Delta}{d}$, the ratio of post-modification payments to pre-modification monthly payments. The first row presents summary statistics for loans that were not modified, for which this quantity has been imputed. The second row presents summary statistics on modified loans as they appear in the data.

Change in \$'s Monthly Payment	Percentiles						
	Mean	S.D.	10th	25th	Median	25th	90th
Imputed (Not Modified Loans)	0.710	0.092	0.607	0.642	0.693	0.764	0.846
Actual (Modified Loans)	0.725	0.139	0.538	0.616	0.715	0.837	0.927

Table 4: Borrower's Response to Loan Modification - OLS and IV Estimates

The table displays estimates of the effect of loan modification on borrower level observables. The tables plot estimates of the coefficient β_2 and β_3 from the structural equation $Y_{it} = \eta_{ct} + \psi_{(t-t_0(i))} + \beta_1 X_{it} + \beta_2 Modify_i + \beta_3 Modify_i \cdot \mathbf{1}_{t_m(i) > t} + \epsilon_{ict}$. Note that the data are in a panel setting with multiple time serious observations (t) for each loan (i). For columns 2 and 3 the sample used is 30 Year Fixed Rate Mortgages from the McDash LPS data that become 90+ days delinquent at some point in their history. For columns 4 and 5, the sample is further restricted to loans for which a match is available in the ABSNet Loan and GSE datasets so as to obtain the identity of the mortgage servicer and Originator. "Modify" is an indicator variable equal to 1 if the loan is modified at any point following serious delinquency. "Modify x Post" is equal to 1 if the loan i is modified following serious delinquency and the time period t corresponds to one following the loan modification of mortgage i . Column 1 presents, for a comparison, the average change in 6 months worth of monthly payments are a result of the loan modification. Column 2 presents results from an OLS estimation of the structural equation, with no additional control variables, Column 3 adds County by Time Fixed Effects, Time Since Delinquency Fixed Effects, and control variables. Column 4 adds Originator by Securitizer (PLS or GSE) Fixed Effects. Column 5 implements the instrumental variables approach using two stage least squares. Panel A has as the dependent variable the auto-purchase indicator variable while Panel B has the dollar value of auto purchases as captured by the credit bureau data based proxy. Panel C has as dependent variable the unsecured spending proxy variable, while Panel D presents results using the Equifax Vantage Credit Score as a dependent variable.

Panel A: Auto Purchase Indicator					
	(1)	(2)	(3)	(4)	(5)
		OLS	OLS	OLS	2SLS
VARIABLES		New Car Ind.	New Car Ind.	New Car Ind.	New Car Ind.
Avg. Change in Mthly. Pmt.	-2160				
Modify		-0.0047*** (0.0003)	-0.0004 (0.0003)	-0.0005 (0.0005)	-0.0021 (0.0047)
Modify x Post		0.0313*** (0.0004)	0.0173*** (0.0005)	0.0165*** (0.0007)	0.0237*** (0.0089)
Observations		6,829,752	6,093,074	2,377,684	2,441,457
R-squared		0.0031	0.0157	0.0259	0.0252
Controls		No	Yes	Yes	Yes
Controls x Linear Trend		No	Yes	Yes	Yes
County by Time FE		No	Yes	Yes	Yes
Time Since Delinquency FE		No	Yes	Yes	Yes
Originator by Securitizer FE		No	No	Yes	Yes
Borrower FE		No	No	No	No
Partial 1st Stage F-Stat		-	-	-	95
Clustering		County	County	County	County
Panel B: Auto Purchase (\$)					
	(1)	(2)	(3)	(4)	(5)
		OLS	OLS	OLS	2SLS
VARIABLES		New Car \$	New Car \$	New Car \$	New Car \$
Avg. Change in Mthly. Pmt.	-2160				
Modify		-97.3885*** (6.7271)	-17.3017** (7.6317)	-14.6708 (13.0669)	40.8895 (100.0215)
Modify x Post		625.6580*** (11.2206)	337.6254*** (10.2331)	337.8889*** (15.4260)	427.6917** (198.3280)
Observations		6,829,752	6,093,074	2,377,684	2,441,457
R-squared		0.0014	0.0088	0.0292	0.0282
Controls		No	Yes	Yes	Yes
Controls x Linear Trend		No	Yes	Yes	Yes
County by Time FE		No	Yes	Yes	Yes
Time Since Delinquency FE		No	Yes	Yes	Yes
Originator by Securitizer FE		No	No	Yes	Yes
Borrower FE		No	No	No	No
Partial 1st Stage F-Stat		-	-	-	95
Clustering		County	County	County	County

Table 4: Borrower's Response to Loan Modification - OLS and IV Estimates

Panel C: Non-Durable Consumption (Proxy) (\$)					
	(1)	(2)	(3)	(4)	(5)
		OLS	OLS	OLS	2SLS
VARIABLES		NonDur	NonDur	NonDur	NonDur
Avg. Change in Mthly. Pmt.	-2160				
Modify		-83.7063*** (8.0843)	-46.7914*** (4.0093)	-33.9333*** (6.8132)	-110.6914* (66.8499)
Modify x Post		22.8642*** (4.0232)	56.9709*** (6.7047)	73.8934*** (8.4656)	263.9607*** (78.4031)
Observations		6,829,752	6,093,074	2,377,684	2,441,457
R-squared		0.0002	0.0440	0.0553	0.0550
Controls		No	Yes	Yes	Yes
Controls x Linear Trend		No	Yes	Yes	Yes
County by Time FE		No	Yes	Yes	Yes
Time Since Delinquency FE		No	Yes	Yes	Yes
Originator by Securitizer FE		No	No	Yes	Yes
Borrower FE		No	No	No	No
Partial 1st Stage F-Stat		-	-	-	95
Clustering		County	County	County	County
Panel D: Credit Score					
	(1)	(2)	(3)	(4)	(5)
		OLS	OLS	OLS	2SLS
VARIABLES		Credit Score	Credit Score	Credit Score	Credit Score
Avg. Change in Mthly. Pmt.	-2160				
Modify		-0.9687 (0.7752)	8.6261*** (0.5281)	10.3303*** (0.6416)	27.7345*** (3.4293)
Modify x Post		30.7287*** (0.5311)	10.8214*** (0.2774)	9.7222*** (0.3908)	4.1742 (3.4479)
Observations		6,829,563	6,092,903	2,377,636	2,441,405
R-squared		0.0208	0.1235	0.1320	0.1279
Controls		No	Yes	Yes	Yes
Controls x Linear Trend		No	Yes	Yes	Yes
County by Time FE		No	Yes	Yes	Yes
Time Since Delinquency FE		No	Yes	Yes	Yes
Originator by Securitizer FE		No	No	Yes	Yes
Borrower FE		No	No	No	No
Partial 1st Stage F-Stat		-	-	-	95
Clustering		County	County	County	County

Table 5: Robustness to Heterogenous Treatment Effects

Panel A: Ex-Ante Credit Score				
	(1)	(2)	(3)	(4)
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
<u>Incremental Cash Flows From:</u>				
Interest from PMTs	0.1781 (0.0530)	0.1653 (0.0495)	0.1484 (0.0455)	0.1323 (0.0402)
Principal from PMTs	0.0771 (0.0196)	0.0789 (0.0190)	0.0779 (0.0182)	0.0761 (0.0170)
Principal at Termination	-0.2439 (0.1106)	-0.2159 (0.1054)	-0.1973 (0.1051)	-0.1819 (0.1045)
Gains to Investor	0.0105 (0.1260)	0.0264 (0.1167)	0.0289 0.1139	0.0286 (0.1114)
Panel B: Change in House Prices between Orig. and 90+				
	(1)	(2)	(3)	(4)
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
<u>Incremental Cash Flows From:</u>				
Interest from PMTs	0.1208 (0.0400)	0.1353 (0.0430)	0.1693 (0.0453)	0.1771 (0.0449)
Principal from PMTs	0.0707 (0.0169)	0.0687 (0.0169)	0.0728 (0.0163)	0.0833 (0.0157)
Principal at Termination	-0.1235 (0.0622)	-0.1423 (0.0629)	-0.2090 (0.0536)	-0.3472 (0.0875)
Gains to Investor	0.0681 (0.0754)	0.0591 (0.0786)	0.0318 (0.0752)	-0.0835 (0.1039)
Panel C: Origination Loan Amount				
	(1)	(2)	(3)	(4)
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
<u>Incremental Cash Flows From:</u>				
Interest from PMTs	0.0765 (0.0271)	0.1536 (0.0476)	0.1448 (0.0490)	0.1355 (0.0500)
Principal from PMTs	0.0379 (0.0118)	0.0761 (0.0191)	0.0762 (0.0198)	0.0771 (0.0200)
Principal at Termination	-0.1183 (0.1068)	-0.2042 (0.1043)	-0.1914 (0.1015)	-0.1810 (0.0988)
Gains to Investor	-0.0032 (0.1139)	0.0282 (0.1143)	0.0314 (0.1111)	0.0325 (0.1085)

Table 6: Sensitivity to Key Assumptions

	(1) $\Delta PV(\text{Interest PMTs})$	(2) $\Delta PV(\text{Principal PMTs})$	(3) $\Delta PV(\text{Principal Termination})$	(4) Gains	(5) Across CBSA by Time SD of Gains
Foreclosure Discount $\varphi = 1$	0.1587 (0.0552)	0.0744 (0.0241)	-0.5361 (0.1460)	-0.3029 (0.1557)	(0.1480)
Foreclosure Discount $\varphi = 0.65$	0.1587 (0.0552)	0.0744 (0.0241)	-0.1710 (0.1117)	0.0621 (0.1245)	(0.0500)
Perfect Foresight House Prices	0.1587 (0.0552)	0.0744 (0.0241)	-0.2406 (0.1098)	-0.0073 (0.1221)	(0.1080)
Higher rate (40%) of post mod redefault	0.1587 (0.0552)	0.0744 (0.0241)	-0.2476 (0.1005)	-0.0144 (0.1140)	(0.0570)

A Appendix Figures and Tables

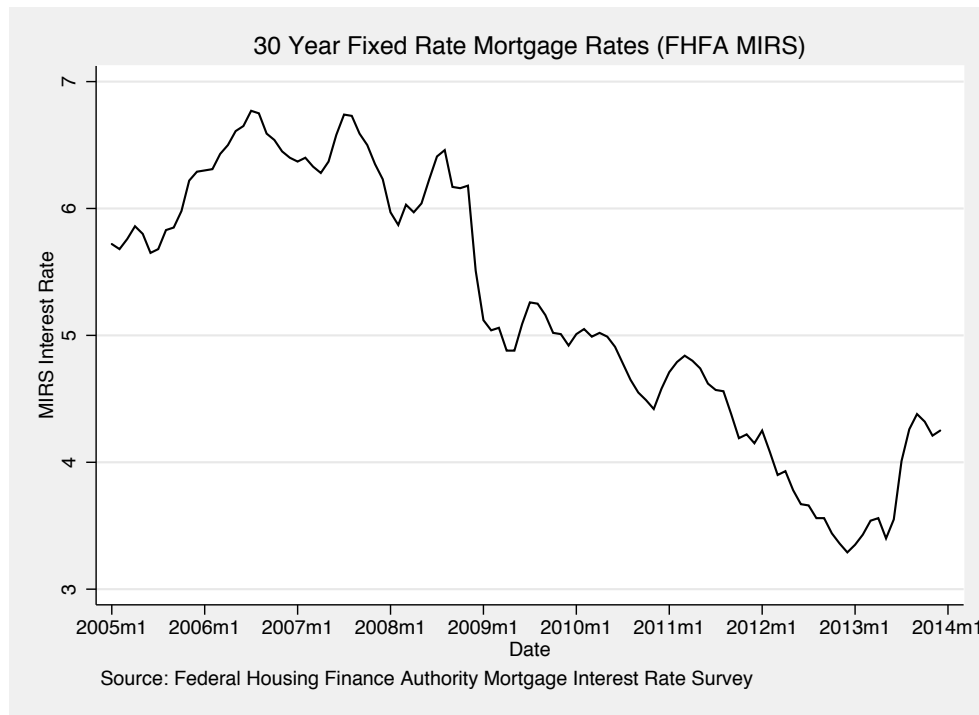


Figure 11: Across CBSA by time of delinquency variation

The graph above plots the time series of the Federal Housing Finance Authority's Mortgage Interest Rate Survey.

$$\underbrace{\sum_{k=1}^{T_{Mod}} \frac{\Delta}{(1+R_1)^k}}_1 + \underbrace{\sum_{k=T_{NoMod}}^{T_{Mod}} \frac{d}{(1+R_1)^k}}_2 = \underbrace{\Delta PV(PMTs)}_3$$

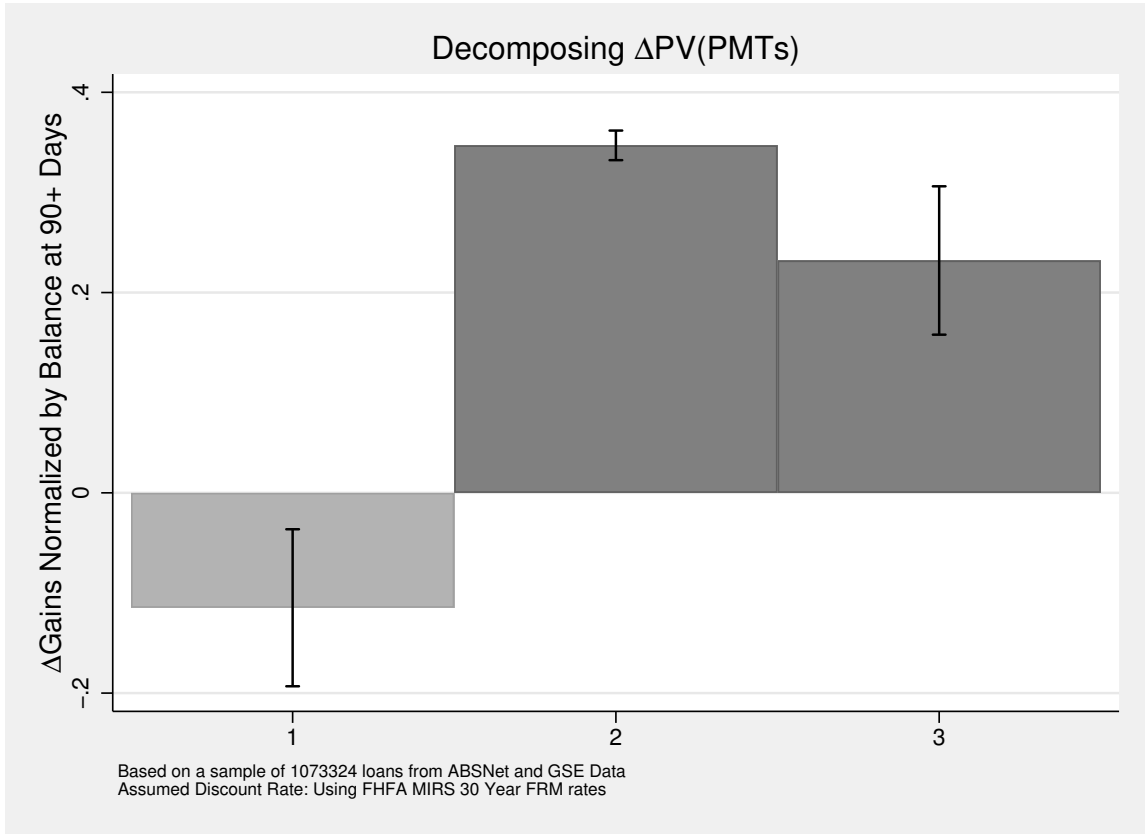


Figure 12: Decomposing the gains from monthly payments

This graph shows the mean and variance of the gains from modification to investors relative to not modifying the mortgage that arise from the continued payment of monthly interest and principal. The bar graphs represent the means of normalized estimated gains which are measured at the loan level. The lines represent 95% confidence intervals based on the conditional standard deviation of the loan level estimates of gains from modification. The bars denote various components of $\Delta PV(PMTs)$ as depicted in the formula above the chart. The estimates are based on my analysis on data on 30 Year Fixed Rate mortgages from ABSNet Loan, and the publicly available Fannie Mae and Freddie Mac data.

$$\underbrace{\underbrace{\frac{(1+R_1)^{T_{NoMod}}}{(1+R_1)^{T_{Mod}}}}_1 \underbrace{\left(\frac{G(P_1, D_{T_{Mod}})}{(1+R_1)^{T_{NoMod}}} \right)}_2}_3 - \underbrace{\frac{\phi P_1}{(1+R_1)^{T_{NoMod}}}}_4 = \underbrace{\Delta PV(\text{Termination})}_5$$

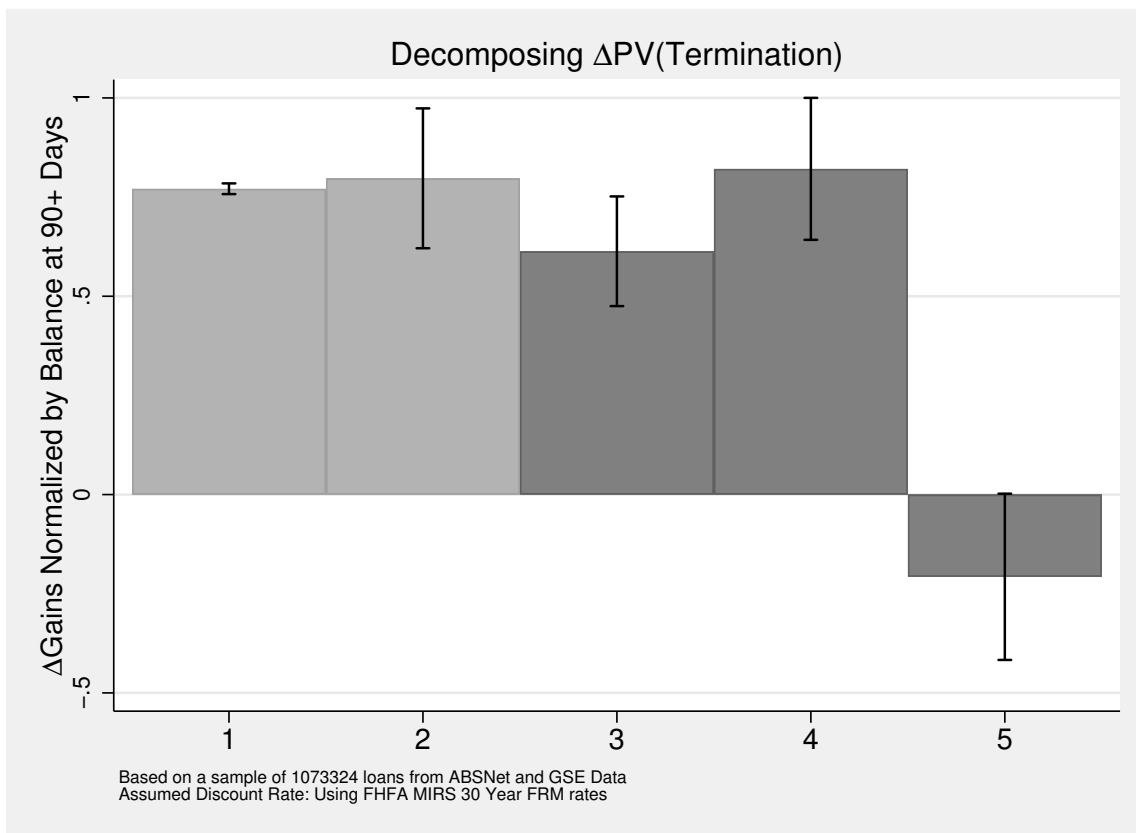
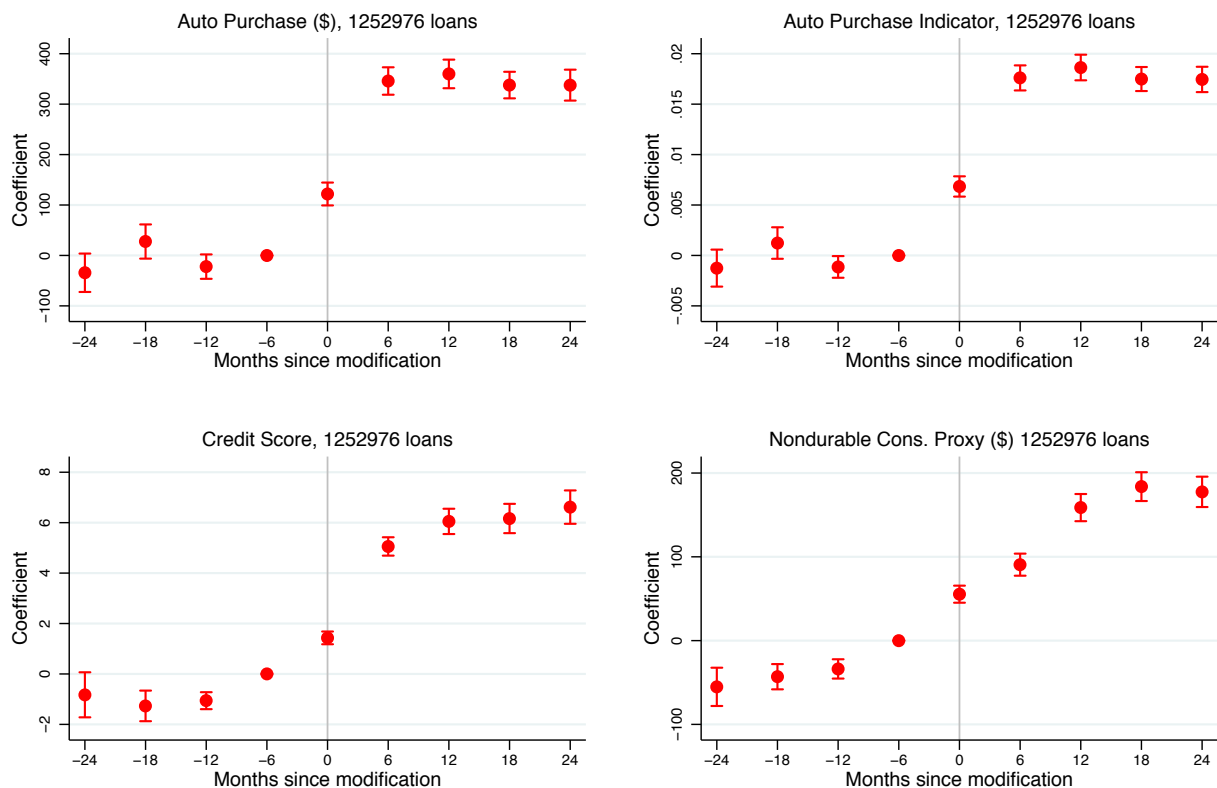


Figure 13: Decomposing the gains from termination

This graph shows the mean and variance of the gains from modification to investors relative to not modifying the mortgage that arise from the continued payment of monthly interest and principal. The bar graphs represent the means of normalized estimated gains which are measured at the loan level. The lines represent 95% confidence intervals based on the conditional standard deviation of the loan level estimates of gains from modification. The bars denote various components of $\Delta PV(\text{Termination})$ as depicted in the formula above the chart. The estimates are based on data on 30 Year Fixed Rate mortgages from ABSNet Loan, and the publicly available Fannie Mae and Freddie Mac data.



The graphs above show estimates from an OLS regression with county by calendar halfyear fixed effects. Includes loan level controls and allows for differential time trends for different observables.
Source: LPS–Equifax 30 Yr FRMs

Figure 14: Borrower’s Consumption Response to Loan Modification - OLS Estimates

The graphs above plot results from an event study estimation of the effect of loan modification on borrower-level observables. The dependent variables used in the event studies are (clockwise from top): automobile purchases proxy variable (constructed using credit bureau data), indicator variable for whether an auto-mobile purchase was made; non-durable purchases proxy variable; and Equifax Vantage score (credit score) of the borrower from Equifax. The x-axis plots the time since loan modification in 6 month intervals, with the effect of the loan modification in the 6 month interval before modification ($t = -1$) normalized to 0. The loans used in the estimation are 30 Year Fixed Rate mortgages from McDash Loan Performance Services Data that become 90+ days delinquent at some point in their history. Standard errors are clustered at the county level.

Table 7: Summary Statistics for 90+ Days Delinquent Mortgages (Loan Performance Services Data)

The table below displays summary statistics on mortgages that enter the analysis. The loans used to construct the summary statistics are 30 Year Fixed Rate mortgages from the ABSNet Loan Private Label Securitization Data and the Fannie Mae and Freddie Mac publicly available data. The sample is restricted to those loans that become at least 90+ days delinquent at some point in their history. The table displays summary statistics as at the origination of the mortgage, or summary statistics on the type of loan modification obtained.

	LPS GSE Loans			LPS Private Label Securitized		
	N	Mean	SD	N	Mean	SD
FICO \geq 680 (%)	685159	0.51	0.50	255692	0.41	0.49
620 \leq FICO $<$ 680 (%)	685159	0.34	0.47	255692	0.36	0.48
FICO $<$ 620 (%)	685159	0.15	0.36	255692	0.23	0.42
Origination LTV	846021	0.80	0.14	301823	0.78	0.12
LTV at 90+	715485	1.01	0.26	257582	0.98	0.25
Interest Rate	846717	0.07	0.01	303838	0.07	0.02
DTI	846718	21.82	23.00	303838	17.11	21.30
DTI Missing (%)	846718	0.43	0.50	303838	0.55	0.50
Purchase Loan (%)	846718	0.43	0.50	303838	0.38	0.48
Cash Out Refi (%)	846718	0.13	0.33	303838	0.21	0.41
Rate Refi (%)	846718	0.04	0.19	303838	0.02	0.14
Single Family (%)	846718	0.80	0.40	303838	0.80	0.40
Not Primary Residence (%)	846718	0.19	0.39	303838	0.18	0.38
Modified within 6 mths. of 90+ (%)	846718	0.12	0.32	303838	0.16	0.37
Modified within 12 mths. of 90+ (%)	846718	0.19	0.39	303838	0.22	0.42
Modified overall (%)	846718	0.26	0.44	303838	0.29	0.45
Principal Increase (%)	214244	0.88	0.33	79869	0.84	0.36
Rate Decrease (%)	217072	0.83	0.37	77453	0.69	0.46
Term Increase (%)	217760	0.44	0.50	81400	0.14	0.35
Payment Decrease (%)	215935	0.94	0.23	77208	0.81	0.39

Table 8: Consumption and Redefault

The table displays estimates of the effect of automobile purchases on subsequent redefault of a mortgage following loan modification. The table displays estimates from a linear probability model. The loans used in the estimation are 30 Year Fixed Rate mortgages from the LPS McDash dataset that were modified after becoming 90+ days delinquent. The dependent variable is an indicator variable equal to 1 if the borrower becomes 90+ days delinquent at any point following loan modification. “Car Purchase After Mod” is an indicator variable equal to 1 if the borrower purchased an automobile at any point following loan modification, and 0 otherwise. “Car Purchase Before Mod” is an indicator variable equal to 1 if the borrower has purchased an automobile at any point prior to loan modification. Columns 1 to 5 all present estimates from an OLS regression. Each column adds additional sets of control variables. The preferred estimate is from Column 5.

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
VARIABLES	Re-Default	Re-Default	Re-Default	Re-Default	Re-Default
Car Purchase After Mod?	-0.0656*** (0.0026)	-0.0663*** (0.0028)	-0.0494*** (0.0027)	-0.0431*** (0.0026)	-0.0451*** (0.0027)
Car Purchas Before Mod?		0.0039 (0.0029)	0.0156*** (0.0025)	0.0201*** (0.0024)	0.0136*** (0.0025)
Observations	177,027	177,022	177,022	177,022	149,743
R-squared	0.0036	0.0037	0.1357	0.1594	0.1772
Controls	No	No	No	No	Yes
County FE	No	No	Yes	Yes	Yes
Month of Del FE	No	No	No	Yes	Yes
Month of Mod. FE	No	No	Yes	Yes	Yes
Mod Type FE	No	No	No	No	Yes
Cluster	County	County	County	County	County
Mean of Dep Var	0.59	0.59	0.59	0.59	0.59

B Detailed Conceptual Framework

Consider an environment with three periods $t = 0, 1, 2$ where a mortgage has already been originated at $t = 0$ to fund 100% of the purchase of a property worth P_0 . In general, P_t represents the value of the property at time t . The servicer monitors the mortgage in time $t = 1, 2$. Assume that there is no uncertainty or asymmetric information in the model. The borrower has utility over consumption at $t = 1, 2$. Each period he has Cobb-Douglas utility over units of goods, c_t , and units of housing, c_{th} , consumed. The borrower's utility function will be given by:

$$U(c_1, c_{1h}, c_2, c_{2h}) = (c_1)^{1-\alpha}(c_{1h})^\alpha + (c_2)^{1-\alpha}(c_{2h})^\alpha \text{ with } \alpha \in (0, 1)$$

One additional assumption will be that borrowers cannot adjust their consumption of housing c_{th} after it has been chosen at $t = 0$ upon origination of the loan (i.e., $c_{1h} = c_{2h} = c_h$). Thus, I focus on the units of consumption goods consumed by the borrower, c_t , a proxy for which I can observe in the data. The borrower receives income \bar{y} in each period from which he makes his mortgage payments, and consumes some minimum level of the consumption good \underline{v} . Assume the mortgage contract is such that the borrower has to make two equal periodic payments, d , at times $t = 1, 2$ and consequently repay all outstanding principal, D_2 , at the end of $t = 2$.⁴⁶

At $t = 1$, there will be a permanent unexpected income shock with the income realization now being $y_1 = \tilde{y} < \bar{y}$. I restrict attention to the interesting case where $\tilde{y} < d + \underline{v}$.⁴⁷ This formulation captures the inherent incompleteness of a mortgage contract.⁴⁸ Now the servicer makes a decision about whether to modify the loan or not.

Suppose the mortgage is not renegotiated and the borrower is foreclosed upon. Then, the borrower's consumption bundle is $c_1 = \tilde{y} - \rho c_h - \theta$; $c_2 = \tilde{y} - \rho c_h$ where ρ is the rental cost of one unit of housing. At $t = 1$, the borrower does not make his monthly payment, but consumes the same level of housing c_h for which he now pays rent. Additionally, he bears a

⁴⁶The initial lending takes place in a perfectly competitive mortgage market, with all lenders earning zero profits, therefore I have the condition $d + d + D_2 = P_0$. Moreover, assume the asset pricing equation, $P_0 = \rho c_h + \rho c_h + P_2$ holds, where ρ is the rental cost of housing and c_h is the flow of housing units from a property worth P_0 . Therefore, in equilibrium $d = \alpha \bar{y} = \rho c_h$ and $D_2 = P_2$ and $c_1 = (1 - \alpha)\bar{y}$; $c_2 = (1 - \alpha)\bar{y}$; $c_h = \frac{\alpha \bar{y}}{\rho}$.

⁴⁷If $\tilde{y} > \tilde{y} \geq d + \underline{v}$ the borrower can still make his monthly payment. The inefficiency that arises from not being able to rewrite the contract is the failure of the borrower to smooth consumption over period 1 and period 2.

⁴⁸In this setting, given the assumed lack of ex-ante uncertainty, the contract will be non-contingent when originated. I follow [Eberly and Krishnamurthy \(2014\)](#) in modeling the unexpected income shock to capture such incomplete contracting frictions in a reduced form manner.

cost of being in default of θ . Let θ represent costs such as loss of access to credit markets, relocation costs and other fees and expenses the borrower bears by being in foreclosure. If the servicer forecloses upon the borrower, the investor simply recovers ϕP_1 where $1 - \phi \in (0, 1)$ represents the property value recovered from a foreclosure sale. The investor receives nothing at $t = 2$.

Now consider the borrower's consumption bundle and the investor's cash flows when the loan does get renegotiated. Let the renegotiation involve an adjustment of the borrower's monthly payment, Δ , such that he is able to remain current; i.e., Δ s.t. $\tilde{y} \geq d + \Delta + \underline{v}$.⁴⁹ Then, the borrower's consumption bundle is $c_1 = \tilde{y} - (d + \Delta)$; $c_2 = \tilde{y} - (d + \Delta)$. Note here that the borrower also does not bear the cost of default, θ . If he has paid down enough of his principal, $D_2 \leq 90\% \times P_2$, I assume that he simply refinances the mortgage and repays the principal outstanding. The investor receives D_2 at the end of $t = 2$. However, if the borrower is sufficiently underwater, $D_2 > 90\% \times P_2$, he will be unable to refinance, and will enter foreclosure to repay the principal outstanding. In this case, the investor receives ϕP_2 . Let the function $G(P, D)$ denote this terminal cash flow, where $G(P, D) = \mathbf{1}_{\{0.9 \times P < D\}} \cdot \phi P + \mathbf{1}_{\{0.9 \times P \geq D\}} \cdot D$. Following a loan modification, the investor's cash flows can be expressed as $d + \Delta + d + \Delta + G(D_2, P_2)$.

Let $V(\Delta)$ refer to the investor's cash flows from $t = 1$ onwards assuming the loan is modified, and $V(0)$ denote the investor's cash flows assuming the loan is not modified. I express the gains to the investor as:

$$V(\Delta) - V(0) = d + d + \Delta + \Delta + G(D, P_2) - \phi P_1$$

The ability of debt renegotiation to generate gains for the investor will depend on what he can earn from not renegotiating (ϕP_1); on the number and size of additional monthly payments ($d + \Delta$) he collects; on the borrower's ability to pay down the debt until he refinances or redefaults ($G(D, P_2)$). In the case of redefault; the property value at $t = 2$ will also affect the gains. In a setting with discounting, the more delayed the termination, the lower will be the contribution of $G(D, P_2)$ to the present value of gains. On average, a loan modification extends the time over which mortgage debt is repaid (Eberly and Krishnamurthy (2014)) by lowering the interest rate (often to a level below the average rate on a new mortgage), extending the term of the loan, capitalizing missed payments into the balance (increasing D_2), and engaging in principal forbearance.⁵⁰ It keeps the borrower current on the mortgage,

⁴⁹Note that this assumption of a permanent income shock is not crucial to my goal of estimating the benefits to investors and borrowers. It will just affect what the optimal loan modification might look like.

⁵⁰Principal forbearance happens when some portion of the outstanding balance is converted into interest

but delays recovery of principal.

Similarly, defining the consumption bundle of the borrower with modification as $W(\Delta)$ and without modification as $W(0)$, I can write down the incremental consumption bundle from loan modification as:

$$W(\Delta) - W(0) = (-2\Delta + \theta)$$

Borrowers consume from the decrease in monthly payments due to the loan modification (-2Δ) . Additionally, they avoid the costs of being in foreclosure, θ .⁵¹ In this case, θ might represent the continued access to credit markets due to the avoidance of foreclosure, which better allows borrowers to smooth consumption.

C Data Restrictions

As I describe in the main text, I restrict analysis to 30 Year Fixed Rate Mortgages to reduce the distance between my assumptions and the empirical setting. In addition, making this assumption will reduce the false positive and false negative errors of the modification detection algorithm employed in the LPS data which is used to select the sample from the credit-registry. Finally, two of these datasets do not directly identify principal forbearance, i.e., where a portion of the outstanding balance is converted into interest-free debt. Principal forbearance can easily be inferred from data on 30 Year Fixed Rate loans using the standard mortgage annuity formulae.

One potential disadvantage of this restriction is that delinquency rates for 30 Year Fixed Rate Mortgages were lower than those for loans with features such as adjustable rates ([Amromin et al. \(2011\)](#)). In drawing positive conclusions, restricting attention to a simpler contracting space is beneficial. In drawing normative conclusions however, concerns about external validity to other types of mortgage contracts will caveat the results. However, these concerns may be mitigated by the fact that most adjustable rate mortgages were renegotiated into fixed rate loans and not into more complex mortgage contracts.

A number of papers have identified the difference in the rate of modification between loans that were securitized and those that were held on banks' balance sheets, and so I restrict my analysis to loans that were securitized (either in private-label securitizations or securitized by Fannie Mae and Freddie Mac). Furthermore, I restrict my sample to loans that were

free debt, without the amortization term of the loan being changes. This results in a balloon payment upon maturity of the contract.

⁵¹Also note that ρc_h and d cancel out. The initial contract in this frictionless world will result in $d = \rho c_h$ in equilibrium

originated between and including the years 2004 to 2007. When using data from LPS I restrict to years 2005 to 2007 due to poor availability of data prior to 2005. Additionally, I leave loans that enter the LPS data after more than 12 months from origination to reduce bias from seasoning effects. I further restrict the sample to loans that went seriously delinquent before 2012. Finally, a loan will enter my analysis when it becomes 90+ days delinquent, i.e., the borrower misses three or more monthly payments.

D Imputing modifications for loans that are not modified

While the success of loan modification depends on the ability of the servicer to extend the life of the mortgage by reducing monthly payments by Δ , this reduction also has a negative effect on the cash flows to the investors. For loans that were modified, I simply observe Δ in the data. For those that were not, I infer the change in the mortgage contract using the parameters from two regressions:

$$\mathbf{1}_{\{\Delta Contract_i \neq 0\}} = X_i' \eta_1 + \epsilon_i \quad \text{if } Modify_i = 1 \quad (12)$$

$$\Delta Contract_i = X_i' \eta_2 + \epsilon_i \quad \text{if } Modify_i = 1 \text{ and } \Delta Contract_i \neq 0 \quad (13)$$

where $Contract_i \in \{Rate_i, Balance_i, RemainingTerm_i, InterestFree_i\}$ and represents various terms of a mortgage contract, and $\Delta Contract_i$ is the change in the term from before to after loan modification. The first three contract terms are standard.⁵² $InterestFree_i$ represents the percentage of outstanding balance at the time of serious delinquency that was converted to interest free debt as a result of the modification. I estimate Equation (12) using a probit regression, and Equation (13) using ordinary least squares. X_i includes borrower and loan level observables at origination, and also includes time of delinquency fixed effects, CBSA fixed effects and servicer by time of delinquency fixed effects.

I use predicted probabilities from the first regression and multiply them by predicted values from the second regression to infer $\Delta Rate_i$, $\Delta Balance_i$, $\Delta RemainingTerm_i$, $\Delta InterestFree_i$ for loans with $Modify_i = 0$, and then construct $\widehat{\Delta}_i$ for each of these loans.

With the estimates from Section 3.1 and D in hand, I will be able to compute the gains to investors at the loan level, i.e., compute $(V(\widehat{\Delta}) - V(0))_i$. To facilitate comparison across mortgages, I normalize this estimate by the balance outstanding at the time of entry into serious delinquency to obtain $\frac{(V(\widehat{\Delta}) - V(0))_i}{D_{1,i}}$. With borrower level estimates, I can characterize

⁵² $Rate_i$ is the interest rate on the mortgage, $Balance_i$ is the log of the outstanding balance, $RemainingTerm_i$ is the number of months until maturity of the loan.

both the mean and variance of these gains.

E Consumption Proxy Data

To analyse the consumption response, I use the McDash Loan Performance Services (LPS) data matched to credit bureau data from Equifax. The LPS data covers about 65% of U.S. mortgage originations, with reliable coverage from June 2005 onwards. This data is reported by mortgage servicers who are part of the LPS platform. The dataset contains loans that are securitized (private label as well as GSE, FHA and Ginnie Mae loans) and those held on banks' balance sheets. One disadvantage of this data is that it does not identify the mortgage servicer. To do so, I merge this data with the above two datasets.⁵³ I use the contract change algorithm of Adelino et al. (2013) to identify modifications from the monthly performance data.

In order to estimate the gains to borrowers, I require a measure of consumption. While I do not directly observe borrowers' consumption levels, I construct proxies for their durable and non-durable consumption using data on the liability side of the borrowers' balance sheet. The proxy for durable consumption is constructed using data on automobile financing accounts as in Keys et al. (2014) and Di Maggio et al. (2014). If I observe a discrete change in the balance of automobile finance accounts that is greater than \$5,000 and is accompanied by an increase in the count of automobile financing accounts, I record this as an automobile purchase.⁵⁴

To construct a measure of non-durable consumption, I would ideally require data on the monthly payments made by borrowers on debt such as bank cards or other consumer debt. Unfortunately, the data does not include these variables, although I do observe the outstanding balance on these accounts at a monthly frequency. Thus, I follow the methodology of Di Maggio et al. (2014) who proxy for non-durable consumption using the measure $NonDur_{it} = \mathbf{1}_{\{Unsecured_{it} - Unsecured_{i,t-1} > \$500\}} \cdot (Unsecured_{it} - Unsecured_{i,t-1})$ for borrower i in month t . I consider the borrower to have increased expenditures on non-durable consumption if I observe the unsecured credit balance recorded in Equifax ($Unsecured_{it}$) increase by more than \$500 in a given month. The use of such a proxy suggests that the estimated

⁵³The procedure for the merge is described in Appendix Section H. Also note that I propose an alternative test which does not involve knowing the identity of the servicer.

⁵⁴Di Maggio et al. (2014) describe how about 80% of car purchases are financed, with this proportion remaining consistent over time. Moreover, given that my sample consists of delinquent borrowers, I expect this proportion to be higher in this data. Any automobile purchases that are carried out using cash would not be captured by this proxy variable, but they are likely to be small in number.

response of loan modification on borrower's consumption will be a lower bound on what the true response is likely to be.

F Estimating the effect on consumption

The first specification I use to test for the effect of renegotiation on consumption of the borrower restricts attention to those who received loan modifications.

$$Y_{ict} = \eta_{ct} + \gamma_i + \psi_{(t-t_0(i))} + \beta_1 X_{it} + \sum_{k=-4}^4 \beta_{2k} \text{Modify}_i \cdot \mathbf{1}_{t=t_m(i)+k} + \epsilon_{ict} \quad (14)$$

Here Y_{ict} denotes a measure of borrower level durable or non-durable consumption. This specification represents an event study wherein I control for all time-invariant heterogeneity at the borrower level (γ_i), all time-varying heterogeneity at the county level (η_{ct}), time-since-delinquency fixed effects $\psi_{(t-t_0(i))}$, and borrower and loan characteristics at origination interacted with a linear time trend (X_{it}). Modify_i is an indicator variable equal to 1 if the loan was modified, and $\mathbf{1}_{t=t_m(i)+k}$ is an indicator variable for whether time t is k periods ahead of time $t_m(i)$, i.e., the date when the loan was modified. Note that coefficient $\beta_{2,-1}$ is restricted to be 0. Each time period t will cover 6 months.

The coefficients of interest are $\{\beta_{2k}\}_{k=-4}^4$, where each coefficient measures the Y_{ict} at time $t = k$ relative to Y_{ict} at time $t = -1$. In this specification, I use within borrower time-series variation to identify the effect of renegotiation. However, this specification does not control for selection into loan modification, which may be dependent on unobservable characteristics. The results of this analysis appear in Figure 9.

The next specification I turn to is similar to Equation 14, but I now include all loans that did not receive a loan modification. The estimating equation is:

$$Y_{it} = \eta_{ct} + \psi_{(t-t_0(i))} + X'_{it}\beta_1 + \sum_{k=-4; k \neq -1}^4 \text{Modify}_i \cdot \mathbf{1}_{t=t_m(i)+k} \cdot \beta_{2k} + \epsilon_{ict} \quad (15)$$

The absence of borrower fixed effects γ_i implies that I am using variation across borrowers to identify the coefficients $\{\beta_{2k}\}_{k=-4}^4$. I now use as a control group those borrowers who have also become 90+ days delinquent, do not receive a loan modification, but equally deep into their delinquency. By looking at the coefficients for event times $t < 1$ facilitates a comparison of their consumption patterns before the loan was renegotiated. The results of this specification appear in Appendix Figure 14.

The estimated $\{\beta_{2k}\}_{k=-4}^4$ from this specification will be biased due to endogenous selection of loans into renegotiation, i.e., $Cov(\text{Modify}_i \times \mathbf{1}_{t=t_m(i)+k}, \epsilon_{ict} \mid \eta_{ct}, \psi_{(t-t_0(i))}, X_{it}) \neq 0$. To overcome this selection bias, I will use a two stage least squares framework, incorporating an instrumental variable to obtain exogenous variation in loan modification. Since the data on consumption is rather noisy, I move away from an event study setting, and test for the change in consumption from before the loan modification to after the loan modification. Yet, I maintain the essential ingredients of Equation (15). The structural equation to be estimated is:

$$Y_{it} = \eta_{ct} + \psi_{(t-t_0(i))} + X'_{it}\beta_1 + \underbrace{\text{Modify}_i\beta_2 + \text{Modify}_i \cdot \mathbf{1}_{t_m(i)>t} \cdot \beta_3}_{\text{Instrumented}} + \epsilon_{ict} \quad (16)$$

The coefficient of interest is β_3 . The two first stage regressions will be:

$$\begin{aligned} \text{Modify}_i &= \eta_{1,ct} + \psi_{1,(t-t_0(i))} \\ Z'_{it}\lambda_1 + X'_{it}\lambda_2 + \xi_{ict} \end{aligned} \quad (17)$$

$$\begin{aligned} \text{Modify}_i \cdot \mathbf{1}_{t_m(i)>t} &= \eta_{2,ct} + \psi_{2,(t-t_0(i))} \\ &+ Z'_{it}\gamma_1 + X'_{it}\gamma_2 + v_{ict} \end{aligned} \quad (18)$$

where Z_{it} is a vector that is excluded from Equation (16).⁵⁵ In other words, variation in Z_{it} is assumed to be independent of a borrower's consumption decisions. That is, Z_{it} only drives them through its effect on whether and when a loan gets modified. Using predicted values from the first stage regressions in place of Modify_i and $\text{Modify}_i \cdot \mathbf{1}_{t_m(i)>t}$ in Equation (16) will allow me to estimate $\hat{\beta}_{3,IV}$. The results of this specification appear in Table 4.

G Censored Regression Framework

Deriving the log-likelihood and average partial effect

Recall that the model was given by

⁵⁵ Angrist and Pischke (2008) suggest the use of a linear probability model in the first stage to avoid model mis-specification.

$$T^* = \beta \cdot m + \epsilon \text{ where } \epsilon \sim N(0, \sigma_\epsilon^2) \quad (19)$$

$$T = \begin{cases} T^* & \text{if } Censored = 0 \\ T^{max} & \text{if } Censored = 1 \end{cases} \quad (20)$$

$$Modify = \mathbf{1}_{\gamma Z + v > 0} \text{ where } v_i \sim N(0, \sigma_v^2) \quad (21)$$

and where $Cov(\epsilon, v) \neq 0$

where m is an indicator variable equal to 1 if the loan is modified. $T^{max} = 360$ for loans that were not censored and T^{max} equals the observed data for loans that are censored. First, ignore the endogeneity (equations 21) and consider the censored regression model of equations 19 and 20. I wish to derive the log-likelihood function, and the expression for obtaining the average partial effect of loan modification on the number of monthly payments made by a borrower following entry into serious delinquency. I abstract away from other control variables used in the model. First, I obtain an expression for the likelihood of observing a given T_i depending on whether a loan observation is censored (i.e. loan has not left the sample as at December 2013) or not censored.

The cdf of the latent variable T^* will be:

$$\begin{aligned} P(T^* \leq \tau) &= F_{T^*}(\tau) \\ &= P(m \cdot \beta + u \leq \tau) \\ &= \Phi\left(\frac{\tau - m \cdot \beta}{\sigma}\right) \end{aligned}$$

which implies that the pdf is:

$$f_{T^*}(\tau) = \frac{1}{\sigma} \phi\left(\frac{\tau - m \cdot \beta}{\sigma}\right)$$

If the loan is censored, the true realization of the latent variable T^* is not observed. Rather,

some loan specific upper bound, T^{Max} will be observed.

$$\begin{aligned} P(Censored = 1) &= P(T^* > T_i^{max}) = 1 - F_{T^*}(T^{max}) \\ &= 1 - \Phi\left(\frac{T^{max} - m \cdot \beta}{\sigma}\right) \\ &= \Phi\left(-\left(\frac{T^{max} - m \cdot \beta}{\sigma}\right)\right) \end{aligned}$$

Therefore, the log likelihood for observation i can be written as:

$$\log f(T_i | \beta, \sigma) = Censored_i \cdot \log \Phi\left(-\left(\frac{T_i^{max} - m \cdot \beta}{\sigma}\right)\right) + (1 - Censored_i) \cdot \log\left(\frac{1}{\sigma} \phi\left(\frac{T_i - m_i \cdot \beta}{\sigma}\right)\right)$$

Since m is a binary variable, the average partial effect can be expressed as $E[T | m = 1] - E[T | m = 0]$. $E[T | m]$ can be expressed as:

$$\begin{aligned} E[T | m] &= P(Censored = 1 | m) \cdot T^{max} + P(Censored = 0) \cdot E[T | T < T^{max}, m] \\ &= \Phi\left(-\left(\frac{T_i^{max} - m \cdot \beta}{\sigma}\right)\right) \cdot T^{max} + \Phi\left(\frac{T^{max} - m \cdot \beta}{\sigma}\right) \cdot [m\beta + E[u | T < T^{max}, m]] \\ &= \Phi\left(-\left(\frac{T_i^{max} - m \cdot \beta}{\sigma}\right)\right) \cdot T^{max} + \Phi\left(\frac{T^{max} - m \cdot \beta}{\sigma}\right) \cdot \left(m\beta - \sigma \frac{\phi\left(\frac{T^{max} - m \cdot \beta}{\sigma}\right)}{\Phi\left(\frac{T^{max} - m \cdot \beta}{\sigma}\right)}\right) \\ &= T^{max} - (T^{max} - m\beta) \cdot \Phi\left(\frac{T^{max} - m \cdot \beta}{\sigma}\right) - \sigma \phi\left(\frac{T^{max} - m \cdot \beta}{\sigma}\right) \end{aligned}$$

Now, using data on $\{T_i, T_i^{max}, m_i, Censored_i\}_{i=1, \dots, N}$ the average partial effect can be computed as:

$$N^{-1} \sum_{i=1}^N \left[\hat{\beta} \Phi\left(\frac{T_i^{max} - \hat{\beta}}{\hat{\sigma}}\right) + T_i^{max} \left(-\Phi\left(\frac{T_i^{max} - \hat{\beta}}{\hat{\sigma}}\right) + \Phi\left(\frac{T_i^{max}}{\hat{\sigma}}\right) \right) + \hat{\sigma} \left(-\phi\left(\frac{T_i^{max} - \hat{\beta}}{\hat{\sigma}}\right) + \phi\left(\frac{T_i^{max}}{\hat{\sigma}}\right) \right) \right]$$

Deriving the log-likelihood function for censored regression model with endogenous dummy variable

Note that if loan modification were randomly assigned, the average partial effect, would allow me to capture the average treatment effect of loan modification. However, loan modification is not randomly assigned and so I will augment this censored regression model with an endogenous dummy variable. m will be the endogenous dummy variable in this case. I assume that there exists a vector Z_i that is excluded from (19) and is independent of ϵ_i . I assume $m = \mathbf{1} \{\gamma Z + v > 0\}$.

The pdf of the joint distribution of m and T conditional on Z_i will be:

$$f(T, m \mid Z) = f(T \mid m, Z) \cdot f(m \mid Z) \quad (22)$$

$f(m \mid Z)$ will be given by the standard likelihood function for a probit model. Note that there will be four cases in the data.

Case 1: $Censored_i = 0; m_i = 0$

Case 2: $Censored_i = 0; m_i = 1$

Case 3: $Censored_i = 1; m_i = 0$

Case 4: $Censored_i = 1; m_i = 1$

The density $f(T \mid m, Z)$ can be derived for each of these cases. First, the equation for the latent variable T^* can be written as:

$$T^* = \beta \cdot m + \theta v + e_1$$

where, by the joint normality assumption;

$$\epsilon = \theta v + e_1$$

where $\theta = \frac{Cov(\epsilon, v)}{Var(v)} = \frac{\rho_1}{\sigma_v^2}$ and where $Var(e_1) = \sigma_\epsilon^2 - \frac{\rho^2}{\sigma_v^2} \equiv \mu^2$. Upon making this substitution, the density $f(T^* \mid m, Z, v)$ takes the usual censored regression form as derived above. For example, consider the density of T^* , conditional on m , $Z_{S \times t_0}$ and v , in Case 1 and 2 where the data is not censored:

$$f(T \mid m, Z, v) = \frac{1}{\mu} \phi \left(\frac{\tau - m \cdot \beta - \theta v}{\mu} \right)$$

and subsequently in Cases 3 and 4, where the data is censored:

$$f(T \mid m, Z, v) = \Phi \left(- \left(\frac{T^{max} - m \cdot \beta - \theta v}{\mu} \right) \right)$$

Having obtained the likelihood function conditional on v , I now use the fact that $m_i = 1$ if the shock to the latent variable underlying the model, v , is realized to be greater than $-\gamma Z$.

In this case, the density of T conditional on m , and the density of m can be written as:

$$f(T | m, Z) = \frac{1}{\Phi(\gamma Z)} \int_{-\gamma Z}^{\infty} f(T | m, Z, \xi) \phi(\xi) d\xi$$

$$f(m | Z) = \Phi(\gamma Z)$$

Alternatively, if $m_i = 0$:

$$f(T | m, Z) = \frac{1}{1 - \Phi(\gamma Z)} \int_{-\infty}^{-\gamma Z} f(T | m, Z, \xi) \phi(\xi) d\xi$$

$$f(m | Z) = (1 - \Phi(\gamma Z))$$

Putting these expressions together, and considering equation 22, the likelihood functions for each of the four cases of the data can be written as:

$$\text{Case 1: } f^1(T_i; \beta, \gamma, \sigma_e, \sigma_v, \rho_1) = \int_{-\infty}^{-\gamma \Lambda_{S \times t_0}} \frac{1}{\mu} \phi\left(\frac{T_i - m_i \cdot \beta - \theta \xi_i}{\mu}\right) \phi(\xi_i) d\xi_i$$

$$\text{Case 2: } f^2(T_i; \beta, \gamma, \sigma_e, \sigma_v, \rho_1) = \int_{-\gamma \Lambda_{S \times t_0}}^{\infty} \frac{1}{\mu} \phi\left(\frac{T_i - m_i \cdot \beta - \theta \xi_i}{\mu}\right) \phi(\xi_i) d\xi_i$$

$$\text{Case 3: } f^3(T_i; \beta, \gamma, \sigma_e, \sigma_v, \rho_1) = \int_{-\infty}^{-\gamma \Lambda_{S \times t_0}} \Phi\left(-\left(\frac{T_i^{\max} - m_i \cdot \beta - \theta \xi_i}{\mu}\right)\right) \phi(\xi_i) d\xi_i$$

$$\text{Case 4: } f^4(T_i; \beta, \gamma, \sigma_e, \sigma_v, \rho_1) = \int_{-\gamma \Lambda_{S \times t_0}}^{\infty} \Phi\left(-\left(\frac{T_i^{\max} - m_i \cdot \beta - \theta \xi_i}{\mu}\right)\right) \phi(\xi_i) d\xi_i$$

The range of the integration depends on whether the loan has been modified or not modified, and the expression that enters the integration depends on whether the observation for the loan in the data is considered to be censored. Average Partial Effects can be computed as above, using the estimated values of β and σ_e that result from the full maximum likelihood procedure. The maximum likelihood procedure is implemented in Stata using the “cmp” command.

H Matching LPS to ABSNet and GSE data

In order to obtain the names of servicers and originators for loans in the LPS data, I employ a simple algorithm to match the LPS dataset to the ABSNet data on privately securitized mortgages, and the data on 30 Year Fixed Rate Mortgages from Fannie Mae and Freddie Mac. First, I will describe the methodology used to match the LPS dataset to the ABSNet dataset, and then discuss how this is modified when matching to the GSE datasets.

First, for every loan in the LPS dataset, I find loans in the ABSNet dataset that have the same interest rate, five digit zip code, loan amount and first month that a mortgage payment is due. This will result in pairs of mortgages that are identical on these characteristics but might differ on others. At this stage, each LPS loan will be potentially mapped to more than one ABSNet loan. I keep only those pairs for which both borrowers have the exact same FICO score at origination. Then, I keep those pairs for which the loan purpose is the same. Next, I keep only those pairs where the loans have loan to value ratio at origination which is within 2 percentage points of each other. Among the set of pairs that a given LPS loan may still be in, I keep the pair with the least difference in the loan-to-value ratios and the least difference in the credit score. I achieve a match rate of 52%.

Next, I match the LPS sample to the GSE data. I first follow a similar procedure as above. In the first round of matching I obtain pairs of loans with exact matches on interest rate, three digit zip code, loan amount and first month that a mortgage payment is due. Then, I keep only those pairs for which both borrowers have exact same FICO score at origination; then keep those for whom the loan purpose is the same, and then those for whom the LTV at origination is within 2 percentage points of each other. I drop all LPS loans that have not been uniquely paired at this point. Since the data does not go into more granular geographic detail than a 3 digit zip code, I want to minimize matching errors. I trade-off precision of the match with a lower match rate. I achieve a match rate of 47%.