Borrowers Signal, Lenders Respond: The Strategic Value of Foreclosure Delay

Henry Munneke and Nicholas B. Smith*

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Abstract

A lender's decision to foreclose or modify a delinquent loan is often made with incomplete information regarding the borrower's ability to self-cure the delinquency. This informational asymmetry may lead lenders to foreclose or modify loans of borrowers with the ability to self-cure and suffer the high cost of this decision. However, a delinquent borrower may signal their future ability to pay, and desire not to lose a property, by making full or partial payments in an attempt to stave off any lender action even if the loan remains in delinquency. This study examines lenders' reactions to these signals. The results, not surprisingly, show that lenders delay foreclosure in response to the receipt of payments and that the timing of these payments also impact the likelihood of foreclosure, and separately, loan modification. In addition, as more defaulters signal, lenders require a stronger signal to delay action. Finally, we study how laws that force foreclosure delay impact signaling, lender decisions, and the costs of delayed foreclosure. We find that lenders were more likely to foreclose after the law ended and incurred greater costs in the presence of the foreclosure delay law.

* The University of Georgia, Terry College of Business – Munneke (hmunneke@uga.edu) and Smith (Nicholas.smith@uga.edu)

Introduction

Many transactions occur, and contracts finalized, under conditions of incomplete or asymmetric information. In some cases, it may be beneficial to one party, or both parties, if one party reveals their own private information to the other party. This strategic signaling is an attempt by the signaler to influence the behavior of the party receiving the signal. Signaling is especially important in repeated games as prior signaling will influence responses to future signals. Real Estate mortgage contracts allow a unique opportunity to observe signaling beyond the information that an initial signal may convey. We specifically study borrowers signaling their intent to pay (self-cure) after defaulting. Adelino et al. (2013) note that information on the ability/desire to self-cure is asymmetric and lenders often foreclose rather than negotiate with the borrower due to this asymmetry. However, we observe a significant number of borrowers making full or partial payments after default even though the loan may still remain delinquent, assumingly to signal a future intent to pay and stave off foreclosure. This payment signaling is in line with the work of Spence (1973)[1] which notes that signaling may address asymmetric information by separating, in our case, high-cure and low-cure borrowers. The signals may convey that the borrower has a high probability of curing the delinquent loan without intervention.

The purpose of this study is to explore if lenders respond to payment signals with strategic inaction, as the high cost of foreclosure makes strategic inaction attractive for loans likely to self-cure. Ambrose and Capone (1996) note that inaction is a valuable alternative option for loans with a high self-cure probability given the high costs of modification and foreclosure. We define strategic inaction as lenders allowing loans to linger in delinquency in the presence of signaling. Should a borrower self-cure, the cost of inaction is merely the time cost of the delayed principal less any offsetting fees for missing payments. If the borrower fails to cure, then the cost to the lender is the delayed losses-given-foreclosure.[2] Thus, lenders may strategically delay foreclosing on defaulted loans with sufficiently high self-cure likelihood.[3]

The lender-defaulter dynamic studied is relatively unique in that lenders and borrowers continually signal their likelihood of future choices as well as their likelihood of cooperation in an iterative and repeated signal framework. Due to the costs of foreclosure, strategic lenders and borrowers benefit from some level of cooperation and delaying foreclosure if the borrower may cure soon.

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[1] Note that Spence, Akerlof (1970), and many others study non-repeated games. Real estate mortgages allow studying signals in repeated games as the lender decision repeats each month a borrower remains delinquent.
[2] Modification has similar consequences if the borrower redefaults, highlighting that inaction and modification preserve the contract while foreclosure terminates it. Delaying these costs would only increase them should house prices fall further when the lender forecloses.
[3] Strategic inaction is different from formal forbearance agreements which resemble loan modifications.

Cooperation by the lender involves delaying foreclosure in exchange for a future cure. Periodic payments while the loan is delinquent signals cooperation by the borrower through the payment of interest and possibly some principal. This default-foreclosure process represents an iterated prisoner's dilemma. Axelrod and Hamilton (1981) show that, unlike one-time prisoner dilemmas, cooperation in iterated dilemmas may lead to a Nash equilibrium and depends on the expected strategy of the opponent.[4] In cases where a player expects some level of cooperation, a Nash equilibrium exists for the "tit-for-tat" strategy which states a player mimics the other player's strategy and cooperates if the other agent cooperates. Borrowers signaling cooperation who have defaulted may encourage the lender to cooperate and delay foreclosure.

Brosig (2002) studies the effects of signaling on games such as the Prisoner's Dilemma and finds that the Nash Equilibrium of immediate defection (foreclosure in this case) depends on a lack of information on the other agent. If agents may credibly signal an intent to cooperate in a repeated Prisoner's Dilemma, then both parties cooperate. These results depend on the credibility of the signal and the willingness to cooperate. Payments signal effectively if the payments are large, recent, or frequent enough to credibly signal an intent to pay and cooperate.

Prior literature shows that signaling influences the profit maximizing or cost minimizing agent. Ndofor and Levitas (2004) study the strategic firm with a knowledge advantage over competitors. Firms use signaling to inform external stakeholders of their knowledge advantage without transferring that knowledge to other firms. Signaling is also a common theme in international politics literatures. Horowitz et al. (2017) show that countries adopting a military conscription policy are more likely to be accepted into alliances. States wishing to join such alliances signal commitment and lower costs to the current alliance members by increasing the size of their own military. In both literatures, an agent/firm/state influences the behavior of external parties by revealing private information to the other party. In much the same way, borrowers signal lower costs to the lender and a desire to retain the property.

Lenders themselves already recognize the value of delaying foreclosure through a 90-day delinquency standard before initiating foreclosure proceedings. Costs associated with foreclosure are high, and the current study's data indicates that, on average, foreclosure costs constitute over 9% of the proceeds from an REO sale. Further, Ambrose and Capone (1996) note that 75% of loans reaching a 90-day delinquency will ultimately cure and completion rates of foreclosures are less than 55%. There appears to be strong incentives for lenders to delay acting on defaults. Literature notes increasing

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4 As part of his work on game theory, Axelrod held a contest for other academics to design the optimal response to an iterated prisoner's dilemma. The winning strategy was the "tit-for-tat" strategy designed by Anatol Rapoport.

foreclosure timelines during and after the 2008-2009 financial crisis and largely attributes this to regulation and market frictions (Cutts and Merrill (2008) and Cordell et. al. (2015) among others). However, these extended timelines could also be due to lenders reacting to signals during time of distress. If lenders believe homes will sit vacant as real estate owned due to depressed demand, then there is an additional incentive to leave the borrower in the home if the lender believes the borrower will preserve the asset. This reduces lender costs as the lender is not responsible for upkeep, and we expect defaulters making payments also preserve and value the asset.

We test our hypotheses utilizing loan-level data provided by Fannie Mae (FNMA). This panel data includes acquisition and performance data for each month that Fannie Mae held a given loan. This includes a variable for payments outstanding each month which allows for studying lender responses[5] to delinquencies. We measure the number of payments made by a borrower over the prior 12-months as the signal and then also incorporate timing. The data also contain information on the costs incurred for foreclosed loans. We also narrow our sample to sand states, or Arizona, California, Florida, and Nevada, to study signaling and lender behavior regarding California Foreclosure Prevention Laws (CFPLs).

A Cox discrete-time hazard model, estimated via a multinomial logit model, is used to study lenders' decision making. Deng et al. (2000) identifies the ability of multinomial logit models to capture the exercise of mortgage options. Multinomial logit models are common in the lender literature as they address issues of truncation and censoring in datasets such as ours. Our data contains only loans reaching a severe, 90+day delinquency and we capture whether lenders either foreclose, modify, or do nothing at each delinquency date.

Our results show that an increase in the number of recent payments significantly decreases the likelihood of modification or foreclosure as compared to inaction. We also find that payments made more recently increase the likelihood of modification and decrease the likelihood of foreclosure. We believe these results support our primary hypothesis that lenders respond to payment signals.

In addition to the base effect of payments, we explore if the level of signaling in an area impacts signal effectiveness. In other words, if low-cure borrowers also begin to signal, is seems that high self-cure borrowers are forced to signal even stronger to separate their signal from that of the low self-cure borrower. The data (Figure 1) clearly shows an increase in the number of payments over time. We provide evidence that signals are less effective in areas, zip codes, with high rates of signaling. This result

[5] We note here that the servicer controls these decisions. However, servicers are bound to FNMA by servicing agreements, and we expect them to behave as if they were the lender and will be referred to as the "lender" herein.

is in line with labor economics literature which shows that employers require greater educational attainment to increase earnings as more individuals seek education (Lange 2007).

During 2008-2009, government intervention into real estate increased to address a rise in defaults and foreclosures. These laws typically incentivized modification as an alternative to foreclosure without considering strategic inaction. As a result, many laws extended foreclosure timelines temporarily protecting defaulters from foreclosure. Such laws are typically universal and do not distinguish borrowers by self-cure probability. This temporary protection may distort the information sent through signals. We extend the work of Gabriel et. al. (2021)[6] which studies two California Foreclosure Prevention Laws (CFPLs) enacted in response to the 2008-2009 financial crisis. The first law required upkeep on REO which we refer to as the "Upkeep Law". The second law, the "Delay Law", delayed foreclosures and provided incentives to modify.

The Upkeep Law, passed in July 2008 and was active until January 2013, required upkeep on homes obtained through foreclosure with fines of up to $1,000 per property per day if not kept up.[7] Our policy of interest is the Delay Law which passed in January 2009, became active starting July 2009, and ended January 2011. This law extends the required delinquency period from 90-days from first default to 180-days. Lenders could avoid this additional 90-day moratorium by creating a state-approved modification program. Laws which extend delinquencies, such as the Delay Law, may interfere with signaling and lead to a build-up of delinquent loans.

We believe our study captures several important effects. We find that temporarily extending delinquency timelines lead to a build-up of loans which the lender promptly foreclose on loans after the policy has ended. Our results show that the marginal probability of foreclosure was nearly three times higher in California after the law, as compared to before. We also provide evidence that lenders foreclosed more often during the time between the passage and enactment of the Delay Law.

With regards to signaling, we find that borrowers in California making a higher number of payments were less likely to experience foreclosure after the policies; however, borrowers only making a few payments were relatively more likely to experience foreclosure relative to sand states. Thus, such foreclosure delay policies may increase the importance of signaling to avoid the higher foreclosure rate

[6] Gabriel et. al. show that many foreclosures were prevented due to these laws which provided pecuniary benefits. Our results indicate that lenders paid the cost of those benefits which is FNMA in our case. Given the bailout of FNMA, this means ultimately the taxpayers pay for these kinds of policy.

[7] This law is like Vacant Property Registration Ordinances (VPROs) as studied by Biswas et al. (2021).

between law passage and enactment (a rush to foreclose) and the build-up of loans which the lender promptly forecloses upon after the policy.

We also examine the impact of signaling and policy on the costs associated with foreclosure. High self-cure defaulters signal their desire to avoid foreclosure and retain the property. All else equal, these borrowers will likely take actions to preserve the home's value. Low self-cure borrowers likely lead to greater pecuniary costs of foreclosure and losses to the lender. Laws that universally enforce longer delinquencies also extend the time borrowers with low self-cure are in possession of an asset they are less likely to preserve. Thus, we hypothesize that CFPLs lead to higher pecuniary costs of foreclosure. Our results show that lenders incur greater costs in the time after foreclosure protection has ended.

Gabriel et al. (2021) show that CFPL laws benefit the borrower. Our results show that California lenders incurred an estimated \$2,200 more in foreclosure costs after the policy relative to before the policy. According to RealtyTrac, California had 257,664 foreclosure filings in 2011. Assuming our estimates generalize to other lenders, this implies that lenders suffered an *additional* \$567M in costs in 2011 due to the Delay Law. Regardless of the specific numbers, our results demonstrate that laws benefiting defaulters are costly.

We now present a brief discussion of the literature related to lender decision and cost of market and policy driven delay in Section 2. Section 3 follows with a discussion of the data and our empirical methods. Section 4 presents results while Section 5 presents robustness tests using a propensity score matched sample. We study the effect of signals on lender costs in Section 6 and conclude with Section 7.

2 Literature Review

The current study examines the ability of payment signaling to address information asymmetries. Akerlof (1970) first identified that information asymmetries may lead to market failure in the used car market. Spence (1973) followed Akerlof and identified signaling and screening as solutions to asymmetric information. Screening involves the agent without private information obtaining information distinguishing high- and low-quality agents. Signaling, on the other hand, involves the agent with private information exerting costly effort to differentiate themselves from low-quality agents.

Two important assumptions in Spence's model are that signals must be costly, and the opportunity cost of the signal is less for the high-quality agent. For the current study, Spence's first condition is satisfied due to the cost of the payment which may be especially costly if the lender still decides to foreclose. High self-cure borrowers must not only have a high likelihood of fixing the source of default (such as job loss), but also value their current home and its linkages. Otherwise, the borrowers would remain in default to avoid paying the mortgage of an asset they do not value. If two borrowers have similar financial constraints, the one making the loan payment must have a lower opportunity cost associated with non-housing goods. This shows that Spence's second condition is met as the opportunity cost for the high-cure borrower is lower, all else equal. A separating equilibrium emerges for high self-cure agents making payments. We study how these payments, acting as signals, impact lender decision making.

***Lender Decision Making* -** Ambrose and Capone (1996) identify the costs and benefits of five options in response to a default. Specifically, they identify the probability of self-cure as a significant cost for modification and foreclosure. Ambrose and Capone (1998) note the delay between an initial default and eventual foreclosure and identify characteristics of borrowers likely to reinstate during this delay. Their study distinguishes "trigger-event" defaulters or defaults due to some event, such as job loss, rather than price declines. Trigger-event defaulters self-cure if the defaulter remedies the trigger and raises funds necessary to cure amounts owed. Lenders attempt to identify these trigger-event defaulters to reduce costs.

Interest in lender responses to defaults rose along with the rise in defaults and foreclosure during the 2008-2009 financial downturn. Adelino et al. (2013) study the dearth in renegotiation rates for defaults in this period. Their model shows that information asymmetries surrounding self-cure and redefault after modification leads to lower rates of renegotiation. Voicu et al. (2011) studies loans with low documentation and finds that lenders foreclosed more often on these defaulters. Given the lack of information for these loans, it is unsurprising that lenders foreclosed more often on so-called "low doc" loans. A common theme in the literature is that asymmetries surrounding self-cure impairs lender decision making.

Gerardi et al. (2018) investigate causes for defaults and find that job-loss is equivalent to a 35% drop in home value as a determinant for default. As noted in Ambrose and Capone (1998), these defaults are likely "trigger-event" defaulters. We expect that these would be the type of borrowers that may make payments while delinquent and seeking reemployment in hopes of retaining their home. Foote et al. (2008) study information issues surrounding negative equity defaulters and show that temporary reductions in payment size effectively reduce default probabilities.

Given the costliness of foreclosure, lenders often delay and seek less costly alternatives (Capozza and Thomson 2006). Pennington-Cross (2010) studies determinants of lenders' delaying foreclosure by studying outcomes of loans which already entered foreclosure proceedings. Results of this study show that 40% of loans which enter foreclosure proceedings end up as REO while 13% of loans in foreclosure cured and another 27% paid off the delinquent amounts owed prior to foreclosure completion. Interestingly, greater levels of delinquency prior to foreclosure lead to a higher likelihood of a loan becoming REO; however, the longer a loan lingers in a delinquency the more likely it is the loan will be paid. Examining signaling provides additional insights into these prior findings.

***Foreclosure Delay Costs* -** Another common theme in the literature studies the costs related to delaying foreclosure. The preservation of the underlying asset value is a key consideration for the lender. Moratorium on foreclosure or laws delaying it may create a moral hazard where low-cure borrowers lack the incentive to maintain the home as they do not expect to retain the home. Thus, lenders may face increased maintenance costs due to additional damages for neglected homes. If signalers expect a greater likelihood of retaining their home, then we expect they will exert more effort to maintain and preserve their home. Greater preservation of the underlying asset results in greater proceeds from a foreclosure sale and reduces costs for the lender. Our results support this hypothesis, payment signaling lowers foreclosure costs.

Clauretie (1987) examines government policy and costs, and shows that borrower friendly policies, such as judicial foreclosure, increase legal costs of foreclosure and decrease foreclosure likelihood. Demiroglu et al. (2014) demonstrate that borrowers are more likely to default in states with borrower friendly laws. Wilson (1995) studies foreclosure costs in California during 1992-1995. For each month of foreclosure delay, their results demonstrate a one percent increase in foreclosure costs. Cordell et al. (2015) create a model for time-related foreclosure cost severity which is expanded upon in the current study.[8]

Government policies on foreclosure impact lender decision making and may also impact the future cost of foreclosure and/or modification. Gabriel et al. (2021) present a comprehensive study of the effects of the California Foreclosure Prevention Laws and finds that they increase modification rates while decreasing foreclosure rates. In addition, they estimate that these laws prevented 250,000 foreclosures and generated roughly $300 billion in housing wealth.[9] Although they also find that lenders

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[8] Early research into foreclosure costs focuses on the determinants of lender losses. Evans et al. (1985) find that the loan-to-value ratio best predicts losses-given-foreclosure with race and location also playing significant factors. Thus, signaling may be more effective for borrowers with higher LTVs or in areas with high foreclosure costs. Qi and Yang (2009) extend this literature and find that current LTV is the most important factor for foreclosure losses. This study also shows distressed markets generate the greatest loss severities. Lenders may be more responsive to signals during times of market distress.

[9] This figure is based on an estimate aggregate house price return for homes in California of 5.4% as compared to sand states due to this policy.

spent more on property repair costs while under these laws, they attribute these costs to the REO upkeep laws.

Rucker and Alston (1987) show that foreclosure moratoriums on farms during the Great Depression significantly reduced farm foreclosures. Clauretie and Herzog (1990) follow Clauretie's earlier work and show that judicial foreclosure laws lead to a mean five month increase in foreclosure timelines. Ghent and Kudlyak (2011) examine the use of recourse laws and find that lenders use recourse laws less often in judicial foreclosure states. This study also finds that recourse laws only significantly affect lender decisions regarding defaulters deep into negative equity. This highlights the value of signaling as lenders may be less inclined to seek recourse on defaults likely to cure and capture any expected remaining equity.

3 Data and Methods

Loan-level data are drawn from FNMA's single-family loan performance database which provides data on the initial acquisition as well as monthly observations of the loan's performance. The sample is restricted to 30-year, fixed-rate, fully amortizing mortgages originating between 2000 and 2016. The sample is further restricted to loans which became 90+ days past due and were used to finance a home located in one of the 20 Case-Shiller Indexed cities.[10] We further restrict our sample to loans with origination LTVs greater than 40% or origination amounts greater than $20,000. We expect the omitted loans are likely second mortgages or have some other sort of financing involved. We also remove loans in 3-digit zip code areas that contain less than 2,000 monthly loan observations over the entire sample period. These restrictions result in a base dataset of 441,363 loans with 6,621,782 associated monthly loan observations.

***Lender Decision Making* -** Our primary hypothesis is that lenders respond to signals of self-cure with strategic inaction relative to modification and foreclosure. We utilize the number of payments a borrower made over the prior 12 months as the signal of self-cure. As the data reports the lender's actions at monthly intervals, we employ a multinomial logit framework to assess the following Cox discrete-time, competing-risks model based on Deng et al. (2000). Such a model may be written as,

$$\ln(p_{ijt}/p_{i0t}) = \delta_0\, \alpha_{ijt} + \delta_j \boldsymbol{x_{ijt}} + \varepsilon_{ijt} \qquad j = 1,2 \qquad (1)$$

where p_{ijt} is the probability of either modification (j=1) or foreclosure (j=2) relative to the probability of inaction, p_{i0t} (j=0), for loan i at mortgage time t. The variable α_{ijt} represents the baseline probabilities of

[10] The 20 Case-Shiller cities are: Atlanta, Boston, Charlotte, Chicago, Cleveland, Dallas, Denver, Detroit, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa and Washington, D.C

modification and foreclosure. The vector $\boldsymbol{x}_{ijt}$ represents various covariates expected to influence lender decision making, including both time-varying and time-invariant covariates.

The multinomial logit[11] framework to study a Cox discrete-time, competing-risks model is commonly used in the mortgage termination literature both in studies of borrower and lender behavior (Ambrose and Capone (1998); Capozza and Thomson (2006); Pennington-Cross (2010); among others). The current study's multinomial logit framework is described as follows:

$$\Psi_{ijt} = \beta_{0ijt} + \beta_{PMT,ijt}\, Number\ of\ Payments_{ijt} + \beta_{MT,ijt}\, Timing\ of\ Payments_{ijt} + \beta_{X,ijt}\boldsymbol{X}_{ijt} + \beta_{FE,ijt}\boldsymbol{FE}_{ijt} + \varepsilon_{ijt} \quad (2)$$

where Ψ_{ijt} represents the monthly lender decision of foreclosure (2), modification (1), or inaction (0). The variable of interest, *Number of Payments*$_{ijt}$, measures the number of payments made over the prior twelve months for loan *i*. The data contain the current number of payments outstanding each month for each borrower. We use the difference between the current month's payments outstanding and the prior month's payments outstanding as the number of payments made. This allows us to capture if a delinquent loan made only a fraction of the outstanding missed payments for a given month.[12] We hypothesize that a greater number of payments made signals a higher likelihood of self-cure leading to inaction. Thus, we expect the coefficient on the *Number of Payments* to be negative.

While the number of recent payments is an important control for our model, the timing of the payments also likely plays a role in the lender's decision. Thus, to attempt to capture/control for the effect of the timing of the payments, we include controls for the *Timing of Payments*. We construct several alterative variables to control for the timing of the payments within the models we estimate. One such variable is *Meantime*, which is defined as the number of monthly payments for each observation weighted by the nearness in time of those payment to the current period and then divided by the sum of the number of payments made over the prior 12 months. Specifically, we define *Meantime* as:

$$Meantime_{itk} = [\Sigma\ w_{ik}\ x\ Number\ of\ Monthly\ Payments_{ik}] \ /\ Number\ of\ Payments_{ik} \quad (3)$$

where *Number of Monthly Payments* is the number of payments borrower *i* made *k* months ago as of time *t.* and *Number of Payments*$_{ik}$ represents the simple sum of payments made over the prior 12 months. The index *k* ranges from 1 to 12. The current month is defined as $k = 1$. Currently, we use a straight-line weight, $(13 - k)$, to define w_{ik}. A second method used to control for the timing of the payments is to

[11] This model corrects for left truncation and right censoring issues noted in mortgage literature.
[12] For example, a borrower had six payments outstanding in month t-1 and three outstanding in month t. We identify this as having made four payments in month t (inclusive of the month t payment plus three outstanding).

"bucket" the number of monthly payments into the recent quarter in which they were made. We hypothesize that more recent payments reduce foreclosure likelihood. Payments and timing may also cause lenders to modify certain loans making payments. For example, a borrower making a few payments and then failing to continue may indicate the borrower's ability to pay a lower payment than the current payment.

The vector $\boldsymbol{X}_{ijt}$ denotes loan and borrower controls which includes both time-varying components and static components. Specifically, we include variables for origination loan amount, current LTV, borrower credit score at origination, an indicator for mortgage insurance, the change in the Case-Shiller index in the loan's MSA over the past six-months, the change in interest rates since origination, and time since the loan first went 90+DPD. A vector of six fixed effects, $\boldsymbol{FE}_{ijt}$, are also included to control for location (3-digit zip code areas), loan servicer, loan purpose, property type, origination year, and delinquency year. These effects make the lender's decision effectively random for a given servicer by location, time, purpose, and property type which addresses endogeneity issues respective to these fixed effects.

Table 1 provides summary statistics for the full lender decision sample based on monthly loan observations as well as at the loans observations at the time of first default/origination.

[Table 1]

On average, loans that were ultimately foreclosed have the lowest average number of monthly payments while loans that were modified made the most. This pattern remains even when the number of payments is calculated over each of the prior 4 quarters. Properties of modified loans were found in MSAs with higher average number of FNMA loans while foreclosed loans were in areas with a lower average number of FNMA loans. This is in line with literature suggesting lenders foreclose less often in areas in which they have high concentrations of loans. Foreclosed loans have the highest average LTVs at a level 10 percentage points above the average LTV of modified loans and loan where no action is taken. Foreclosed loans also have the highest percentage of loans with mortgage insurance while loans not acted upon had the least. Interestingly, foreclosed loans and modified loans have virtually identical average months since default.

4 Results

Signaling and Timing Estimates Based on National Loans - Our primary hypothesis is that lenders respond to signals of self-cure by foreclosing less often on these loans. To test this hypothesis, we estimate a Cox discrete-time hazard model within a multinomial logit model, eq 2. The reference category model is lender inaction which serves as the base category for the lender actions of modification and foreclosure. These estimation results are presented in Table 2.

[Table 2]

Model 2.1 controls for the number of payments the lender received within the prior 12 months (*Number of Payments*).[13] The results indicate that a greater magnitude of payments made in the past 12 months significantly decreases the probability of foreclosure relative to strategic inaction. The likelihood of modification is found to increase, relative to inaction, as the number of payments increases.

To examine the impact of timing, we introduce the variable *Meantime* in model 2.2. Contrary to model 2.1, model 2.2 shows that an increase in the number of payments reduces the likelihood of both modification and foreclosure, holding the timing of the payment constant. The coefficients on the *Meantime* variable indicate that payments occurring nearer in time significantly decreases the probability of foreclosure relative to inaction by the lender, while payments occurring nearer in time significantly increase the likelihood of modification relative to inaction.

To further investigate the effect of the timing of payments, Model 2.3 includes controls representing the number of payments received each quarter. Our results indicate that more recent signals shift the lenders' decision to inaction. Payments made one quarter prior decrease the likelihood of both foreclosure and modification. However, as signals fall further beyond this first quarter, the likelihood of modification increases relative to inaction and the likelihood of foreclosure increases in magnitude relative to the first quarter estimate but is still negative relative to inaction. This indicates that more recent payments demonstrate a higher likelihood of cooperation. This result also follows Anatol Rapoport's Tit-For-Tat equilibrium as the lender will cooperate only so long as they feel the borrower will cooperate.

The sign and significance for the general control variables are consistent across all models. More concentrated lenders, measured by the number of FNMA loans in an MSA, are significantly more likely to modify relative to inaction. Larger origination amounts significantly increase the relative likelihood of modification while decreasing the relative likelihood of foreclosure. Lenders modify less often and foreclose more often on loans with higher current LTVs and higher credit scores relative to inaction. Lenders are also less likely to act on loans with greater numbers of months in delinquency. These results are consistent with prior studies.

[13] We also tested the model using a 24- and 36-month window which returned similar results. The magnitudes of coefficients were slightly smaller due to capturing payments further into the past.

To further clarify the interpretation of our estimates, we calculate the Average Marginal Effects (AME) for Model 2.2 and 2.3 and report them in Table 3.[14]

[Table 3]

For Model 2.2, *Number of Payments* has a significantly positive AME for inaction and significantly negative for modification and foreclosure. Interestingly, this model also indicates that, holding the number of payments made fixed, payments received nearer the current time increase the probability of modification while recent payments marginally decrease the probability of modification and foreclosure. The *Meantime* model seems unable to capture the effect of the nearest time of payments. The results in quarters 2-4 are consistent with the *Meantime* results. However, if we look at the estimates of the prior quarter, nearest the current period, the results indicate recent payment increase the probability of inaction and decrease the probability of foreclosure.

Figures 2-5 present conditional marginal effects (CME) for Model 2.3. Figure 2 calculates the marginal effect of an additional payment in Q1, Q2, Q3, or Q4 on the likelihood of inaction, modification, or foreclosure, assuming the borrower had made no payments in the past 12 months.

[Figure 2]

Assuming the delinquent borrower made no payments, making a payment in the most recent quarter reduces the likelihood of foreclosure by nearly 4 percentage points. This effect largely disappears for payments in Q2-Q4. These results also show that a payment in the most recent quarter does not impact the decision to modify. Figure 3 presents the conditional marginal effect of an additional payment in one of the four quarters of inaction assuming the borrower had made 0-3 payments in each quarter. These results show the impact of the additional payments vary based on the timing of signaling.

[Figure 3]

Figure 4 presents the same CMEs as Figure 3 only now it is the conditional marginal effect on modification.

[Figure 4]

[14] We use AMEs as these are preferred in the literature over marginal effects at means (Bartus (2005); Cameron and Trivedi (2010)) The marginal effects at means were also calculated, though not reported, and are consistent with the AME results.

Figure 4 highlights the complexity of signaling and modification revealed. In all cases, when a borrower has made no payments or many payments (3 payments per quarter), the marginal effect of an additional payment increases as the further into the past the payment has been made. We attribute this to lenders identifying these borrowers as ones who will not be able to self-cure without a modification to the terms of their loan.

Figure 5 presents the conditional marginal effect on foreclosure.

[Figure 5]

Not surprisingly, the foreclosure results mirror the inaction results. An additional payment in Q1 significantly reduces the likelihood of foreclosure and this effect diminishes if the additional payment is made beyond the prior quarter.

These results, combined with the log odds results, clearly demonstrate the power of signaling to reduce the likelihood of foreclosure. Regardless of the number of payments delinquent borrowers made in each quarter, a single payment in the most recent quarter reduces the likelihood of foreclosure up to 4%. Timing has an interesting impact on modification as lenders modify loans that made some payments within the past 12 months, but not in the most recent quarters. We expect this reflects that these borrowers are signaling an ability to pay a less costly mortgage. Overall, these results show that lenders foreclose on low-cure borrowers and weigh modification, or inaction based on whether the borrower will self-cure without intervention.

It seems reasonable to assert that as the market absorbs information on the effectiveness of signals, more borrowers will start signaling. Based on this assertion, we hypothesize that lenders will require greater signaling to extend delinquency as more borrowers' signal and the reaction to signals becomes known. To test this effect, we introduce a variable identifying areas with higher-than-average levels of payments made nationally, *High Payments Zip*. *High Payments Zip* equates to 1 for borrowers residing in a 3-digit zip code where more payments are made on average in a year than the national average. We expect a positive coefficient on *High Payments Zip* showing that lenders act more often (requiring more signaling) in areas with high rates of signaling.

[Table 4]

The results, presented in table 4, show a significantly positive coefficient on *High Payments Zip* for modification and foreclosure. Based on the interaction coefficient we see that in high payment areas, additional payments lead to a lower likelihood of modification relative to inaction than in low payment areas. In addition, in high payment areas, additional payments lead to a higher likelihood of foreclosure relative to inaction than in low payment areas. For delinquent homeowners in high payment zip codes, this shows payments/signals are less effective at reducing foreclosure and less effective at signaling the value of modification.

Signaling and Government Intervention – To examine the impact of the California Foreclosure Prevention Law delaying foreclosure (Delay Law), we now limit the loans in our sample to those originated in the "sand states" of Arizona, California, Florida, and Nevada. This approach leverages the state lines and the timing of the policy to create a border/regression discontinuity design using California loans as the treated group with Arizona, Nevada, and Florida as the untreated.[15] Recall that the Delay Law was passed in January 2009, became active starting July 2009, and ended January 2011. To focus on the time surrounding this event, we create two samples for our analysis.

First, we identify a subsample of delinquent loans within one year of the Delay Law *ending* (January 2010-January 2012) which captures the period 12 months before and after the *end* of the policy.

Second, we identify delinquent loans that were delinquent 18 months before the policy started and 18 months after it ended.[16] The second subsample contains three distinct periods: The 12 months before the passage of the law in January 2009 (January 2008 – December 2008), the 6 months between the passage of the law and its implementation (January 2009 – June 2009), and the 18 months after the end of the Delay Law (January 2011-June 2012). We note that nearly the entire period of our focused subsamples are subject to the Upkeep Law which began in July 2008. Also, the Home Affordable Modification (HAMP) began in the summer of 2012. By subsampling in this way, we attempt to avoid any confounders with respect to the Upkeep Law and other regulations targeting delinquencies.

To identify the treatment effect, fixed effects representing the treatment area (e.g., California) and the time after the end of the period of interest are introduced. The estimates on these fixed effects identify the treatment effect of being a seriously delinquent loan in California with respect to the Delay Law as compared to sand states. The policy specification uses the same variables as in equation (2) only now we include the above noted fixed effects and interactions between them. Such a model can be written as below.

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[15] Since state lines are fixed, we assume that treatment is exogenous and agents outside California cannot manipulate borders to receive treatment. We also assume no other variables are discontinuous at the boundary to satisfy the second condition of a border discontinuity design. This framework has been used in several prior studies to examine California laws.

[16] This creates a subsample between January 2008 and June 2012 excluding observations that occurred while the Delay Law was active.

$$\Psi_{ijt} = \beta_{0ijt} + \beta_{1ijt}\, CA_{ij} + \beta_{AP,ijt}\, (CA_{ij}\ X\ \textbf{Policy}_{\,it}) + \beta_{APP,ijt}\, (CA_{ij}\ X\ \textbf{Policy}_{\,it}\ x\ Number\ of\ Payments_{ijt})$$

$$+\ \boldsymbol{\beta}_{Z,ijt}\boldsymbol{Z}_{ijt} + \varepsilon_{ijt} \qquad (4)$$

where CA_{ij} is the treatment fixed effect for California and $Policy_{it}$, is the fixed effect for the post policy period. Note that for ease of presentation, we only explicitly include the new policy variables relevant to our policy hypotheses in eq 4 and absorb the original control variables, *Number of Payments, Meantime*, fixed effects, into the vector $\boldsymbol{Z}$. We also interact *Policy* with *Number of Payments* to identify the effect of policies on signals. The coefficient, $\beta_{AP,}$ captures the effect of being delinquent in California after the period on interest while the coefficient $\beta_{APP,}$ captures the effect of the policy on signals. If foreclosure prevention laws lead to a build-up in delinquent loans with low self-cure, then we expect a significantly positive coefficient on the interaction of *California* for foreclosure after the end of the law.

To examine how this policy impacts signaling as well as further explore the overall effect of this policy we first focus on the *end* of the Delay Law (Model 5.1). We compare the 12-month period before the end of the Delay Law to the 12-month time period after the end of the policy. By starting 12-months before the ending of the law, borrowers would have surpassed their six-month delay window allowing lenders to actively foreclose on loans.

[Table 5]

These results show that *during* the policy period signals in California significantly reduced the likelihood of foreclosure relative to lender inaction. In other words, the likelihood of foreclosure relative to inaction was lower in California relative to the other sands states. After the end of the policy, a significant difference in the signaling impact is not supported by the estimates (fail to reject). Holding the number of payments constant, we find that after the end of the policy, the likelihood of modification and foreclosure, relative to inaction, are significantly higher in California than in the other sand states. This result is consistent with the idea that the law impeded the ability for the lender to act during the policy resulting in high probability of lender action (foreclosure and modification) once the policy ended.

To further explore the signaling and the impact of the Delay Law, we expand the sample to include the time prior to the law's passage, the time between its passage and enactment, and the time after the end of the law (see model 5.2 in Table 5). The actions of the lender on loans during the law are not included in the sample. With regards to signaling, the only significant coefficient relates to signaling in California after the end of the law. This implies that signaling payments made in the prior 12 months reduced the likelihood of foreclosure immediately after the CFPL law ended.

Interestingly, prior to the passage of the Delay Law the results show California has a significantly lower likelihood of modification and foreclosure relative to other sand states. In the time period between the passage and the start of the law, all the sand states experience a lower likelihood of foreclosure than inaction. Although within California the likelihood of foreclosure relative to inaction was lower indicating a higher likelihood of foreclosure relative to other sand states during the period prior the law's enactment. In the post period, we find that the likelihood of foreclosure, relative to inaction, falls in the other sand states, but increases relatively in California; the likelihood of foreclosure increases in California relative to the other sand states post Delay Law.

Setting aside the signaling aspect of the model, we examine the predictive probability outcomes for inside and outside California for each period (Before, Between Pass and Start, and After) related to the CFPL. In Table 6, we report predictive probabilities for inside and outside California for each of the three periods in Model 5.2.

[Table 6]

The predicted probabilities indicate that there was very little likelihood that loans in California would be modified or foreclosed upon. Given our sample consists of FNMA loans, the Delay Law must have been targeted at a different segment of loans. The results show the probability of foreclosure is relatively stable across the three time periods for states outside of California. Within California, the probability of foreclosure within the time from passage to the time it is enacted is nearly double that of the time prior to the passage of the CFPL. Once the law ends, we see that in the state of California this probability is nearly 3 times greater than prior to the law's passage. The probability of modification outside of California increases relative to the period prior to the law's passage. For loans inside California, modification was least likely during the time Between Pass and Start and foreclosure was most likely After CFPL; the probability of modification after the After CFPL increases to nearly 3 times the level it was prior to the law. In other words, we see a significant increase in modification and foreclosure probabilities after the end of the law although the probabilities seem extremely low.

Overall, our study of a policy extending foreclosure timelines paints an interesting picture of how these polices impact lenders. We find that lenders were more likely to act in general on California loans after the policy. We provide evidence that lenders foreclose more often (have higher probability) after the Delay Law ended as well as evidence showing that lenders foreclosed more often in the period between the law being passed (January 2009) and becoming active (July 2009) relative to the time prior to the law's passage. We also provide some evidence that recent payments were more impactful (reduced the relative probability of foreclosure) in California after the law ended. These results imply that lenders are foreclosing and modifying on a buildup of delinquencies once the law allows, and their choice depends on signals. California loans also foreclosed more often and modified less often when experiencing an imminent foreclosure delay of the policy.

5 Propensity Score Matching

While we believe our model is well-specified, we utilize propensity score matching of borrowers by type to provide robustness to our estimates. We create a balanced sample of loans of similar borrowers based on borrower characteristics at first default with a division between high self-cure (greater number of payments made) and low self-cure defaulters. To operationalize this paradigm, we identify borrowers that made at least one payment after first default, and then estimate a logistic regression of the likelihood a borrower made payments after first default. The logistic model is as follows:

$$Z_i = \mu_0 + \mu_{BC}\boldsymbol{BC_i} + \mu_{FE}\boldsymbol{FE_i} + \eta \qquad (5)$$

where Z_i equals 1 if a borrower i made payments after first default. $\boldsymbol{FE_i}$ includes the same fixed effects as in the lender decision models. $\boldsymbol{BC_i}$ is a vector of borrower characteristics measured at first default for time-varying parameters.

We employ nearest neighbor 1-to-1 matching with replacement[17] to generate propensity score calipers and pair borrowers that made payments after first default (treated) with those that did not (untreated). We limit matches to loans in the same 3-digit zip code and within 12 months of first default month. In testing for sample balance, Imai et al. (2008) and Austin (2008, 2009) note inadequacies of using the mean difference t-test as a determinant of sample balance. As an alternative, Rubin (2000) proposes using the standardized difference in means and the ratio of variances for each variable between groups. The standardized difference in means is calculated as:

$$SDM = \frac{(\overline{X_T} - \overline{X_U})}{\sqrt{\frac{S_T^2 + S_U^2}{2}}} \qquad (6)$$

where $\overline{X}_T$ and $\overline{X}_U$ and S_T^2 and S_U^2 represent the means and standard deviations of covariate X for the subsamples of treated and untreated loans, respectively. Following Rubin (2000), a variable is well

[17] Matching with replacement matches allows control loans to match with multiple treatment loans. Matching without replacement may increase bias by matching loans with very different propensity scores if potential matches are exhausted (Dehejia and Wahba 2002). Matching without replacement also introduces bias as it is dependent on matching order. This may be especially true when including calipers for Zip 3 and time. As a result, matching with replacement is preferred for the current study.

balanced if and only if the standardized difference of means falls in the range of (-0.25, 0.25), and the ratio of the variance falls in the range of (0.5, 2). Based on Rubin's tests of balance all covariates in the sample are balanced. Table A1 in the appendix provides the summary statistics evidence of a balance sample for the matched sample of seriously delinquent loans.

Our results show that lenders respond to signals of self-cure by modifying and foreclosing less often on these loans. When we examine the estimates of Models 2.1 to 2.3, in Table 7, based on the balanced sample of loans we note the sign and significance of the coefficients on our variables of interest remain generally consistent with the estimates from the full sample.

[Table 7]

We again find that *Number of Payments* significantly decreases the relative likelihood of foreclosure. One difference in the results is that the estimate on the *Number of Payments* for modification in Model 7.1 is negative and significant, switching signs from the full sample. It should be noted that this estimate is now consistent with the other estimates in the other models, so we expect this difference to be related to the absence of a control for the timing of the payments in Models 2.1. Overall, these results support our primary hypotheses. We provide further robustness in Section 6 by examining the proceeds and costs of a foreclosure. We have several changes to the "other" variables in our models.

6 Lender Proceeds and Costs

Our results show that lenders' decisions are impacted by the number of payments a borrower recently made. We attribute this effect to payments acting as signals of self-cure. If borrowers who signal self-cure take better care of their homes than low self-cure borrowers, the lender should suffer less costs when a high self-cure borrower loan is ultimately foreclosed upon. If policies delaying foreclosure reduce the incentive to signal and introduce moral hazard, then we expect even greater lender losses. For robustness, we study the foreclosure proceeds and costs related to completed foreclosures.

Prior literature, such as Cordell et al. (2015), study lender losses as the net losses-given-default of the foreclosure sale proceeds less the outstanding mortgage balance. However, payments made reduce the outstanding mortgage balance of the loan which may confound our analysis if we study losses-given-default. As a result, we study the realized costs and revenues[18] associated with the foreclosure separately

[18] FNMA data contains data on four costs: foreclosure costs (such as fees related to obtaining title), property preservation costs, asset recovery costs (such as expenses related to removing occupants), and taxes. The data contain four revenues: net sales proceeds (defined as total cash received from the sale as reported on the HUD-1 settlement statement), credit enhancement proceeds (such as mortgage insurance), repurchase make whole proceeds

rather than as one figure net of outstanding mortgage balance. For this analysis we introduce cost information into the sample and narrow the sample to only include loans that foreclosed.[19] This results in a sample of 183,865 foreclosed loans and a subsample of 26,187 foreclosed loans in sand states.[20] Table 8 provides the summary statistics for the foreclosed loan sample which includes foreclosures across the full sample period. The sand state sample period is limited to foreclosures occurring 18 months before and after the Delay Law started.

[Table 8]

The data indicate that foreclosure costs in the 20 Case-Shiller MSAs are 11.86% of the foreclosure revenues and slightly lower in sand states at 7.86%. Foreclosure costs are also 9.73% of the outstanding mortgage balance (OMB) on average and 5.75% for the sand states. This is slightly lower than prior literature which finds foreclosure costs of 11% - 16% of outstanding mortgage balance. Lenders recover, on average, 67.07% of the outstanding mortgage balance via the net proceeds from the foreclosure sale (excluding other revenues such as “ready make whole” proceeds). This is slightly lower in sand states at 59.35%.

Data on foreclosure sale revenues and costs are only observed in the month of foreclosure, so our sample only includes the monthly observation when a foreclosure occurs. A cost regression model studies signals, foreclosure revenues, and foreclosure costs. Our cost model is defined as:

$$Y_{it} = \lambda_0 + \lambda_{PMT}\, Number\ of\ Payments_{it} + \lambda_{MT}\, Meantime_{it} + \lambda_{\boldsymbol{X}}\, \boldsymbol{X}_{it} + \lambda_{\boldsymbol{FE}}\boldsymbol{FE}_{it} + \varepsilon_{it} \qquad (7)$$

where Y_{it} is a lender’s foreclosure revenues or costs for foreclosure i at foreclosure calendar time t. The vectors $\boldsymbol{X}_{it}$ and $\boldsymbol{FE}_{it}$ include the same control variables as in the lender decision model. Time-varying controls as well as the variables of interest are taken as of the month of the foreclosure. We expect that a greater number of payments made results in fewer costs and losses indicated by a significantly negative coefficient on *Number of Payments*. Table 9 gives results for the base costs model as well as results relating to high payment zip codes.

[Table 9]

(such as amounts received under repurchase warranties), and other foreclosure proceeds (amounts other than sales proceeds such as redemption proceeds).

[19] We note that some foreclosures were missing data on costs and proceeds which is why the number of loans in the cost sample is fewer than the total number of foreclosed loans in the lender decision sample. We drop any foreclosures either missing or recording 0 values for proceeds or costs from the foreclosure.

[20] We study foreclosures in sand states across the entire sample timeframe as well as foreclosures in sand states only in the period defined in Table 6, Model 6.2 (period excluding observations during the CFPL period).

Results show that an increase in the *Number of Payments* made significantly reduces the cost of foreclosure while increasing the revenues. The reduction in costs supports our hypothesis that signalers better care for their homes as these costs include the costs of repairs on the REO.

The impact on revenues with respect to timing is positive as the timing of payments is closer to the current period (*Meantime* increases), as the magnitude of the coefficients on *Meantime* and the interaction term with *Number of Payments* are nearly equal.

The impact of the timing of payments (*Meantime*) on cost is modeled as being dependent on the magnitude of the *Number of Payments* made. If the *Number of Payments* is 5 or less, costs decrease as payments are received nearer the current time period (meantime increases). However, if *Number of Payments* is greater than 5, costs increase as meantime increases. While we are not sure of the exact cause of this result, it is based on a sample of foreclosures.

Regarding control variables, loan concentration increased costs and reduced revenues which may capture contagion effects of foreclosure. Larger loans had significantly greater losses and revenues which likely is due to size. Loans with greater current LTVs had significantly lower revenues and costs.

In model 9.2, we identify areas of higher signaling by introducing the *High Payments Zip* variable into our revenue/cost model, eq 7. We find, as in the lender decision model, signals in *High Payments Zip* do not appear to make as meaningful of a separation as in low payment areas. Signaling in *High Payments Zip* areas increases revenue less and increases cost more than in low payment areas.

In Table 10, we study the effect of *CFPL* policies on costs and proceeds by introducing the same *California* and *Policy* fixed effects and interactions from equation (4) into equation (7) to study the effect of policy. We narrow the sample in a similar manner to Model 5.2 and include only foreclosures occurring the 18 months before and after the Delay Law.[21]

[Table 10]

Results show that foreclosure costs were significantly higher for California loans after the Delay Law ended as compared to the time before the law started in both models. A crucial cost included in foreclosure costs is the maintenance and repair costs of the home. This provides evidence that lenders

[21] We note that a paucity of foreclosures near the end of the Delay Law prohibited us from testing Model 6.1.

bore the costs of borrower benefits noted in Gabriel et al. (2021), and that this build-up in delinquent loans during the policy was of higher cost to borrowers.

Turning now to signaling, we find significantly positive coefficients on the interaction of *CA* and *Payments* for costs and proceeds with a significantly negative coefficient for California after the law ended. Borrowers signaling towards the end of the law and after it ended appears to reduce costs even more which supports the hypothesis that payments signal even lower costs when the borrower is protected from foreclosure.

7 Conclusion

This paper extends the robust line of literature on lender decision making by identifying how signaling may address information asymmetries related to a borrower's ability to cure a delinquency. For various reasons such as job loss or divorce, borrowers may default while hoping to quickly cure the delinquency prior to foreclosure. However, information on a borrower's cure likelihood, or self-cure, is asymmetric between borrower and lender. Lenders may unnecessarily suffer significant costs if they modify or foreclose on a high self-cure delinquency (Ambrose and Capone 1996). Spence (1973) details the ability of signaling to overcome such asymmetries. We define the signal to be borrowers making payments while delinquent. If these signals are effective, then we hypothesize lenders are more likely to use the option of strategic inaction in these situations.

An important aspect of signaling is the costliness of the signal. Borrowers making payments while in default forego using these funds elsewhere. Even after making payments, the lender may still foreclose leaving the borrower with nothing. The opportunity cost of these payments and the risk associated with foreclosure satisfies the conditions noted in Spence (1973) to create a separating equilibrium between high self-cure and low self-cure borrowers. Our results show that making a greater number of recent payments leads to a lower likelihood of modification or foreclosure. This supports the notion that lenders strategically extend delinquencies on loans signaling self-cure and an intent to pay.

We also hypothesize that the effectiveness of payments will diminish as more people start making payments to delay foreclosure. Lenders thus require greater signaling to avoid foreclosure. We show that delinquent borrowers in zip codes with above average levels of signaling are more likely to be foreclosed upon relative to inaction. Payments are also less effective in general in these areas. Further, we also study how policies that force delays on foreclosure timelines impact lender decision making.

With regards to lender decision making, we study how California Foreclosure Prevention Laws (CFPLs) impact signals and lender decisions. California enacted two laws in response to an increase in defaults during 2008-2009. The first law mandated upkeep on bank REO which we name the "Upkeep Law". The second law, which is named the "Delay Law" and is the policy of interest, extended an in-place law requiring three-months of foreclosure delay to six. To study these laws, we narrow our sample to "sand states" or Arizona, California, Florida, and Nevada and to the time shortly before, during, and shortly after the Delay Law took effect. Because of the similarity of sand states' experiences prior to and during the 2008-2009 downturn, they are often used to test treatments in one of the respective states including Gabriel et al. (2021). Our results show that lenders foreclosed more often after the Delay Law relative to the prior. We take this as evidence that this law led to a build-up of delinquent loans with low self-cure.

We also examine the effect of signaling and policy on lender costs and losses. We hypothesize that borrowers expecting self-cure better care for their homes. Results show that greater numbers of recent payments lead to fewer lender losses. In areas with greater levels of signaling, recent payments marginally reduced costs less which highlights that signals are less effective at reducing costs when many are signaling. With regards to policy, we find that lenders suffer greater costs after the Delay Law ended, though recent payments resulted in even fewer costs after the law. These results support the notion that lenders bear the cost of laws benefiting borrowers and that signaling effectively demonstrates lower costs.

The COVID-19 pandemic may indicate lessons learned from the 2008-2009 financial crisis that is supported by our results. Rather than encouraging modifications, government policy in the CARES Act targeted forbearance. As the pandemic unfolded, the CARES Act forced formal forbearance programs and prohibited most foreclosures. Forbearance, rather than modification, was also the primary policy objective. These policies assume that borrowers defaulting during the COVID pandemic have a high self-cure likelihood and defaults were largely fueled by COVID uncertainty. Another interesting aspect of the CARES Act is that these were formal forbearance programs rather than lenders' decision of inaction. These policies appear to be effective as the percentage of mortgages 30+DPD returned to historical lows under 4% in late 2021 after a brief spike to near 6% at the start of the pandemic (Federal Reserve Bank of Philadelphia, 2023). Our results show that lenders would already have extended forbearance to high self-cure borrowers. The question for lawmakers comes down to whether the costs borne by lenders/taxpayers due to enforced forbearance is worth the benefit extended to low self-cure borrowers.

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Exhibit A: Tables

Table 1: Summary Statistics for Lender Decision Sample

	Full Sample		Inaction		Modification		Foreclosure	
At Monthly Loan Observation	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Number of Payments (#)	5.64	4.80	5.65	4.84	7.18	3.58	3.98	4.01
Payments 1 Quarter Prior (#)	1.33	1.80	1.35	1.83	1.66	1.24	0.40	0.94
Payments 2 Quarters Prior (#)	1.40	1.52	1.40	1.53	1.81	1.35	0.99	1.35
Payments 3 Quarters Prior (#)	1.67	1.51	1.67	1.52	2.14	1.29	1.44	1.45
Payments 4 Quarters Prior (#)	1.89	1.47	1.88	1.47	2.38	1.17	1.77	1.45
FNMA Loans in MSA (100,000)	1.86	1.11	1.88	1.11	1.91	1.08	1.43	0.78
Current LTV (%)	91.65	29.93	91.12	30.06	90.45	29.32	100.98	30.68
Change in Case Shiller (%)	0.85	0.23	0.86	0.23	0.84	0.22	0.81	0.22
Change in Mortgage Rates (%)	0.72	0.13	0.72	0.13	0.73	0.12	0.72	0.13
Time Since First Default (mo)	9.22	3.32	9.24	3.33	8.87	2.91	8.92	3.24
At Origination								
Origination Amount ($100,000)	2.14	0.97	2.01	0.98	2.36	0.96	1.92	0.92
Credit Score	682.83	55.65	685.67	59.08	683.97	55.05	700.07	55.11
Mortgage Insurance Indicator	26.24	43.99	18.45	38.79	22.03	41.45	30.91	46.21
LTV at First Default (%)	88.36	28.03	71.50	22.36	90.46	26.83	102.34	29.55
Number of Loans	441,363		98,336		159,162		183,865	

Notes: This table presents summary statistics for the sample of FNMA 90+day delinquent loans on properties in 20 Case-Shiller Cities. *Number of Payments* represents the sum of payments made over the past twelve months. *Meantime* is the weighted average timing of the *Number of Payments* where higher values indicate a greater average nearness to the current period.

Table 2: Lender Decision Model Studying the Effect of Signals and Timing

Log Odds Relative to Inaction	2.1: Payments		2.2: Payments and Time		2.3: Quarterly Payments	
	Modify	Foreclose	Modify	Foreclose	Modify	Foreclose
Number of Payments (#)	0.037***	-0.185***	-0.777***	-0.104***		
	(0.001)	(0.001)	(0.006)	(0.006)		
Meantime (mo)			0.068***	-0.002***		
			(0.000)	(0.000)		
Number of Payments ***x*** Meantime			0.012***	-0.001***		
			(0.000)	(0.000)		
Payments 1Q Prior (#)					-0.017***	-0.681***
					(0.002)	(0.003)
Payments 2Q Prior (#)					0.037***	-0.080**
					(0.002)	(0.003)
Payments 3Q Prior (#)					0.059***	-0.046***
					(0.002)	(0.003)
Payments 4Q Prior (#)					0.098***	-0.062***
					(0.002)	(0.003)
FNMA Loans in MSA	0.014	-0.356***	0.031	-0.357***	0.024	-0.268***
(per 100,000 loans)	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)	(0.018)
Origination Amount	0.126***	-0.167***	0.116***	-0.167***	0.127***	-0.156***
(per $100,000)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Current LTV	-0.574***	0.424***	-0.655***	0.429***	-0.564***	0.406***
	(0.020)	(0.019)	(0.021)	(0.019)	(0.020)	(0.019)
Credit Score	-0.214***	0.367***	-0.140***	0.365***	-0.216***	0.352***
(per 10)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Mortgage Insurance FE	0.141***	0.113***	0.158***	0.113***	0.138***	0.112***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
Change in Case Shiller	-0.003***	-0.009***	-0.004***	-0.009***	-0.003***	-0.008***
(past 6 mo)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change in Mortgage Rate	0.579***	-0.258***	0.576***	-0.255***	0.570***	-0.231***
(since orig)	(0.038)	(0.037)	(0.038)	(0.037)	(0.038)	(0.037)
Time Since 1st Default (Mo)	-0.018***	-0.019***	-0.025***	-0.018***	-0.016***	-0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.332***	-3.041***	-2.168***	-3.046***	-0.685***	-3.896***
	(0.084)	(0.089)	(0.087)	(0.089)	(0.084)	(0.090)
Zip 3 FE	X	X	X	X	X	X
Servicer FE	X	X	X	X	X	X
Origination Year FE	X	X	X	X	X	X
Delinquency Year FE	X	X	X	X	X	X
Property Type FE	X	X	X	X	X	X
Loan Purpose FE	X	X	X	X	X	X
Pseudo-R2	0.081		0.122		0.082	
Chi^2	257,000		386,000		260,000	
Observations	6,621,782		6,621,782		6,621,782	

Notes: The estimates above reflect the estimation of a hazard model for lender decision making. The dependent variable is defined by the decision to modify, foreclose, or take no action (the base category). *Number of Payments* represents the sum of payments made over the past twelve months. *Meantime* is the weighted average timing of the *Number of Payments* where higher values indicate a greater average nearness to the current period. Model 2.3 subsets the number of recent payments into the recent quarter that payment was made. Standard errors are in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 3: Average Marginal Effects - Signals and Timing

	Model 2.2			Model 2.3		
	Inaction	Modify	Foreclose	Inaction	Modify	Foreclose
Number of Payments (#)	0.0064***	-0.0027***	-0.0037***			
	(0.0001)	(0.0000)	(0.0001)			
Meantime (mo)	-0.0033***	0.0035***	-0.0003***			
	(0.0000)	(0.0000)	(0.0000)			
Payments 1Q Prior (#)				0.0175***	0.0000	-0.0175***
				(0.0001)	(0.0000)	(0.0001)
Payments 2Q Prior (#)				-0.0006***	0.0009***	-0.0023***
				(0.0001)	(0.0001)	(0.0007)
Payments 3Q Prior (#)				-0.0006***	0.0014***	-0.0012***
				(0.0001)	(0.0001)	(0.0001)
Payments 4Q Prior (#)				-0.0002*	0.0023***	-0.0017***
				(0.0001)	(0.0000)	(0.0001)
FNMA Loans in MSA	0.0084***	0.0009***	-0.0093***	0.0062***	0.0007*	-0.0069***
(per 100,000 loans)	(0.0006)	(0.0004)	(0.0005)	(0.0006)	(0.0004)	(0.0005)
Origination Amount	0.0017***	0.0027***	-0.0044***	0.0011***	0.0030***	-0.0041***
(per $100,000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Current LTV	0.0035***	-0.0150***	0.0115***	0.0025***	-0.0133***	0.0108***
	(0.0007)	(0.0005)	(0.0005)	(0.0007)	(0.0005)	(0.0005)
Credit Score (per 10)	-0.0062***	-0.0033***	0.0096***	-0.0039***	-0.0052***	0.0092***
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Mortgage Insurance FE	-0.0065***	0.0036***	0.0029***	-0.0061***	0.0032***	0.0028***
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Change in Case Shiller (past 6 mo)	0.0003***	-0.0001***	-0.0002***	0.0003***	-0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Change in Mortgage Rate (since orig)	-0.0061***	0.0131***	-0.0069***	-0.0071***	0.0134***	-0.0063***
	(0.0013)	(0.0009)	(0.0009)	(0.0013)	(0.0009)	(0.0009)
Time Since 1st Default (Mo)	0.0010***	-0.0006***	-0.0005***	0.0007***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: Above represents Average Marginal Effects for Models 2.2 and 2.3 in Table 2. *Number of Payments* represents the sum of payments made over the past twelve months. *Meantime* is the weighted average timing of the *Number of Payments* where higher values indicate a greater average nearness to the current period. Model 2.3 subsets the number of recent payments into the recent quarter that payment was made. Standard errors are in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 4: Lender Decision Model – Signaling, Timing & High Payment Area

	4.1: Zip Mean	
Log Odds of Modify or Foreclose Relative to Inaction	Modify	Foreclose
Number of Payments (#)	-0.774***	-0.133***
	(0.006)	(0.007)
High Payments Zip FE	0.106***	0.058***
	(0.015)	(0.011)
Number of Payments ***x*** High Payments Zip FE	-0.008***	0.046***
	(0.001)	(0.002)
Meantime (mo)	0.068***	-0.001***
	(0.000)	(0.000)
Number of Payments ***x*** Meantime	0.012***	-0.002***
	(0.000)	(0.000)
FNMA Loans in MSA (per 100,000 loans)	0.039*	-0.346***
	(0.016)	(0.018)
Origination Amount (per $100,000)	0.116***	-0.167***
	(0.003)	(0.003)
Current LTV	-0.656***	0.421***
	(0.021)	(0.019)
Credit Score (per 10)	-0.139***	0.364***
	(0.005)	(0.005)
Mortgage Insurance FE	0.158***	0.114***
	(0.008)	(0.007)
Change in Case Shiller (past 6 mo)	-0.004***	-0.008***
	(0.000)	(0.000)
Change in Mortgage Rate (since orig)	0.575***	-0.261***
	(0.038)	(0.037)
Time Since 1st Default (Mo)	-0.025***	-0.018***
	(0.000)	(0.000)
Constant	-2.217***	-3.002***
	(0.087)	(0.090)
Zip 3 FE	X	X
Servicer FE	X	X
Origination Year FE	X	X
Delinquency Year FE	X	X
Property Type FE	X	X
Loan Purpose FE	X	X
Pseudo R2	0.122	
Chi^2	387590.2	
Monthly Observations	6,621,782	

Note: The estimates above are based on the estimation of a hazard model for lender decision making. The dependent variable is defined by the servicer's decision to modify or foreclose or take no action (the base category). *High Payments Zip FE* is an indicator for observations located in 3-digist zip codes that, on average, made more payments over the past 12 months than other zip codes on average. This indicates zip codes where the average delinquent borrower is making more payments. Standard errors are in parenthesis. * p<0.05, ** p<0.01, *** p<0.001

Table 5: Lender Decision Model - Signals and Policy Disruptions

Log Odds Modify or Foreclose Relative to Inaction	5.1: End of Policy		5.2: Before and After Policy	
	Modify	Foreclose	Modify	Foreclose
Number of Payments ***x*** Prior to CFPL			-0.900***	-0.029
			(0.030)	(0.020)
Number of Payments ***x*** Prior to CFPL ***x*** CA			-0.066	0.006
			(0.041)	(0.028)
Number of Payments ***x*** CFPL Passage thru Start			0.063**	0.029*
			(0.023)	(0.012)
Number of Payments ***x*** CFPL Passage thru Start ***x*** CA			0.075	-0.047
			(0.049)	(0.032)
Number of Payments (#)	-0.786***	0.039*		
	(0.019)	(0.019)		
Number of Payments (#) ***x*** CA	-0.009	-0.074***		
	(0.007)	(0.008)		
Number of Payments ***x*** After CFPL	-0.048***	0.069***	0.079***	0.161***
	(0.005)	(0.004)	(0.019)	(0.011)
Number of Payments ***x*** After CFPL ***x*** CA	0.008	-0.011	0.058	-0.082**
	(0.010)	(0.011)	(0.041)	(0.028)
CA FE	-0.081	1.864***	-29.052***	-28.137***
	(0.086)	(0.081)	(0.430)	(1.456)
CFPL Between Pass and Start			-1.373***	-1.324***
			(0.221)	(0.102)
CFPL Between Pass and Start X CA			-0.601	0.519*
			(0.461)	(0.242)
After CFPL	0.421***	-0.291***	0.003	-1.512***
	(0.042)	(0.030)	(0.188)	(0.097)
After CFPL X CA	0.217*	0.396***	-0.342	1.050***
	(0.094)	(0.087)	(0.397)	(0.245)
Constant	-1.084*	-2.214***	-1.710***	-0.915**
	(0.531)	(0.642)	(0.434)	(0.327)
Other Controls	X	X	X	X
Zip 3 FE	X	X	X	X
Servicer FE	X	X	X	X
Origination Year FE	X	X	X	X
Delinquency Year FE	X	X	X	X
Property Type FE	X	X	X	X
Loan Purpose FE	X	X	X	X
Pseudo R2	0.0809		0.1220	
Chi^2	256,593		386,106	
Monthly Observations	6,621,782		6,621,782	

Notes: In January 2009, California passed a law (CFPL) requiring lenders to wait six months between issuing a notice of default and notice of sale which made a required six-month waiting period for lenders to foreclose. This law did not take effect until July 2009 and ended in January 2011. The sample for the above estimations is restricted to Sand States (AZ, CA, FL, and NV). Model 5.1 limits observations to those occurring +/- 1 year around January 2011. Model 5.2 limits observations to those between January 2008 and July 2009 and those between January 2011 and June 2012. This is 1.5 years before and after the law took effect and includes the period between CFPL passage and when the law came into effect (*CFPL Between Pass and Start*). The estimates above are based on the estimation of a hazard model for lender decision making. The dependent variable is defined by the servicer's decision to modify or foreclose or take no action (the base category). Standard errors are in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 6: Predictive Margins for Inside and Outside CA Surrounding the CFPL Period

Inaction	Before CFPL Passage	CFPL Between Pass and Start	After CFPL
Outside CA	0.7937*	0.7654*	0.7530*
Inside CA	0.9930*	0.9955*	0.9846*
Modify	Before CFPL Passage	CFPL Between Pass and Start	After CFPL
Outside CA	0.1437*	0.1740*	0.1738*
Inside CA	0.0027*	0.0018*	0.0078*
Foreclosure	Before CFPL Passage	CFPL Between Pass and Start	After CFPL
Outside CA	0.0626	0.0606	0.0732
Inside CA	0.0027*	0.0042*	0.0076*

Notes: In January 2009, California passed a law (CFPL) requiring lenders to wait six months between issuing a notice of default and notice of sale which made a required six-month waiting period for lenders to foreclose. This law ended in January 2011. The above table presents margins for Model 5.2. These are the predictive margins for inaction, modify, and foreclosure for loans inside and outside CA during different time periods. *- $p<0.001$

Table 7: Robustness Using Balanced Sample

Log Odds Relative to Inaction	7.1: Payments		7.2: Payments and Time		7.3: Quarterly Payments	
	Modify	Foreclose	Modify	Foreclose	Modify	Foreclose
Number of Payments (#)	-0.019***	-0.341***	-0.803***	-0.199***		
	(0.001)	(0.002)	(0.006)	(0.013)		
Meantime (mo)			0.060***	-0.001***		
			(0.000)	(0.000)		
Number of Payments X Meantime			0.012***	-0.003***		
			(0.000)	(0.000)		
Payments 1Q Prior (#)					-0.126***	-1.645***
					(0.002)	(0.017)
Payments 2Q Prior (#)					0.003	-0.204***
					(0.003)	(0.006)
Payments 3Q Prior (#)					0.030***	-0.155***
					(0.003)	(0.005)
Payments 4Q Prior (#)					0.069***	-0.110***
					(0.002)	(0.005)
FNMA Loans in MSA	0.003	-0.594***	0.019	-0.596***	0.016	-0.549***
(per 100,000 loans)	(0.018)	(0.036)	(0.018)	(0.035)	(0.018)	(0.035)
Origination Amount	0.054***	-0.190***	0.055***	-0.190***	0.055***	-0.180***
(per $100,000)	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)
Current LTV	-0.642***	0.578***	-0.747***	0.595***	-0.631***	0.540***
	(0.022)	(0.033)	(0.022)	(0.034)	(0.022)	(0.034)
Credit Score	-0.003	0.205***	0.026***	0.204***	-0.006	0.194***
(per 10)	(0.005)	(0.009)	(0.005)	(0.009)	(0.005)	(0.009)
Mortgage Insurance FE	0.164***	0.136***	0.186***	0.133***	0.161***	0.136***
	(0.008)	(0.013)	(0.008)	(0.013)	(0.008)	(0.013)
Change in Case Shiller	-0.006***	-0.007***	-0.008***	-0.007***	-0.006***	-0.007***
(past 6 mo)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Change in Mortgage Rate	-0.031	-0.313***	0.076	-0.311***	-0.036	-0.302***
(since orig)	(0.041)	(0.075)	(0.041)	(0.075)	(0.041)	(0.075)
Time Since 1st Default (Mo)	-0.032***	0.004***	-0.038***	0.004***	-0.029***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.305***	-4.310***	-0.497***	-4.333***	0.833***	-4.557***
	(0.093)	(0.174)	(0.097)	(0.174)	(0.093)	(0.174)
Zip 3 FE	X	X	X	X	X	X
Servicer FE	X	X	X	X	X	X
Origination Year FE	X	X	X	X	X	X
Delinquency Year FE	X	X	X	X	X	X
Property Type FE	X	X	X	X	X	X
Loan Purpose FE	X	X	X	X	X	X
Pseudo-R2	0.081		0.122		0.082	
Chi^2	257,000		386,000		260,000	
Observations	6,621,782		6,621,782		6,621,782	

Notes: The estimates above reflect the estimation of a hazard model for lender decision making using a balanced sample of loans which made payments after first default with those that didn't. A propensity score matching model pairs loans based on borrower characteristics at first default. The dependent variable is defined by the decision to modify, foreclose, or take no action (the base category). *Meantime* is the average timing of payments with greater weight placed on payments made near in time. Standard errors are in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 8: Summary Statistics for Foreclosure Cost Sample

	Full Sample		Sand States	
	Mean	SD	Mean	SD
Foreclosure Revenues ($)	145,474	97,423	154,792	98,742
Foreclosure Costs ($)	17,248	17,893	12,168	12,673
Foreclosure Net Revenue ($)	121,671	84,187	125,477	79,816
Outstanding Mortgage Balance (OMB) ($)	179,925	90,107	211,436	90,202
Losses-Given-Foreclosure ($)	51,699	55,458	68,813	60,369
Ratio of Costs to Revenue (%)	11.86	-	7.86	-
Ratio of Costs to OMB (%)	9.73	-	5.75	-
Ratio of Net Revenue to OMB (%)	67.07	-	59.35	-
Foreclosed Loans (# of loans)	183,865		26,187	

Notes: This table presents the sample of the monthly loan observation when the foreclosure took place which is used for the lender cost regressions. Sand States are defined as Arizona, California, Florida, and Nevada. Foreclosure Net Proceeds is the net sales proceeds of the foreclosure sale excluding revenues (such as ready-make-whole) and costs (such as upkeep) not related to the REO sale. Losses-Given-Foreclosure is defined as LGF = Outstanding Mortgage Balance + Foreclosure Costs – Foreclosure Revenue.

Table 9: Lender Costs Model Studying Signals and Foreclosure Sale Proceeds and Costs

	9.1: Signals		9.2: Zip Means	
Dep. Var.=	Revenue	Cost	Revenue	Cost
Number of Payments (#)	2,087.79*	-1,025.06*	1,962.46*	-1,602.55*
	(497.32)	(149.12)	(498.76)	(148.27)
Number of Payments (#) ***x*** High Payment Zip FE			-220.41*	1,033.00*
			(68.73)	(20.43)
High Payment Zip FE			-951.86	3,851.92*
			(497.72)	(147.96)
Meantime (mo)	-23.09*	-83.50*	-25.94*	-66.75*
	(9.66)	(2.89)	(9.72)	(2.89)
Number of Payments ***x*** Meantime	23.40*	14.715*	24.53*	9.58*
	(8.65)	(2.59)	(8.66)	(2.57)
FNMA Loans in MSA (per 100,000 loans)	-5,028.86*	1159.918*	-5,188.65*	1,059.24*
	(846.24)	(253.35)	(847.44)	(251.92)
Origination Amount (per $100,000)	93,510.44*	4715.80*	93,506.35*	4,744.23*
	(153.19)	(45.86)	(153.19)	(45.54)
Current LTV	-63,899.50*	-3,026.66*	-63,882.30*	-2,605.96*
	(893.41)	(267.47)	(894.13)	(265.80)
Credit Score	-1,032.79*	-721.85*	-1,033.66*	-752.99*
	(208.08)	(62.29)	(208.09)	(61.86)
Mortgage Insurance FE	31,332.50*	174.62	31,322.39*	132.00
	(300.47)	(89.96)	(300.50)	(89.33)
Change in Case Shiller (past 6 mo)	384.93*	-22.21*	385.75*	-20.39*
	(14.50)	(4.34)	(14.50)	(4.31)
Change in Mortgage Rate (since orig)	601.14	265.01	664.59	323.66
	(1,631.71)	(488.50)	(1,631.72)	(485.07)
Time Since 1st Default (Mo)	281.51*	275.58*	282.05*	270.21*
	(8.29)	(2.48)	(8.30)	(2.47)
Intercept	-14,063.71*	-9,082.52*	-12,700.13*	-6,817.29*
	(2,846.72)	(852.25)	(2,885.37)	(857.76)
Zip 3 FE	X	X	X	X
Servicer FE	X	X	X	X
Origination Year FE	X	X	X	X
Delinquency Year FE	X	X	X	X
Property Type FE	X	X	X	X
Loan Purpose FE	X	X	X	X
Adj. R2	0.69	0.20	0.68	0.20
Foreclosures	183,865	183,865	183,865	183,865

Notes: The estimates above are based on the estimation of a model studying costs and revenues of foreclosure sales. The dependent variables in the models are the revenues or costs from a foreclosure sale. *High Payments Zip FE* is an indicator for observations located in 3-digit zip codes that, on average, made more payments over the past 12 months than other zip codes on average. This indicates zip codes where the average delinquent borrower is making more payments. Standard errors are in parenthesis. *-Indicates significance at a 5% threshold.

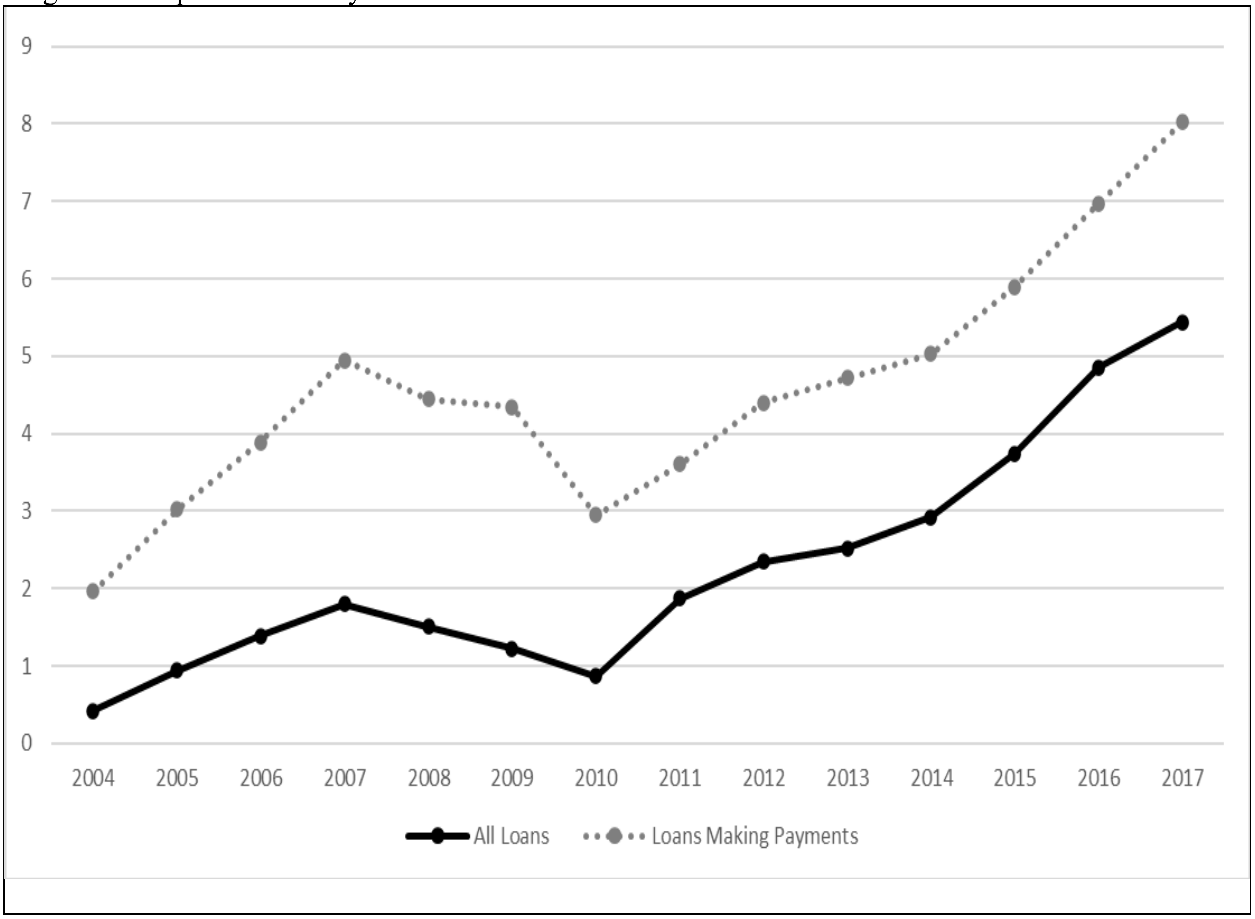
Table 10: Lender Cost Model Studying the Signals, Policy, and Costs Over Time

	10.1: Before and After Policy	
Dep. Var.=	Revenue	Cost
Number of Payments (#)	1,697.05	360.9
	(1,544.49)	(330.57)
Number of Payments ***x*** CA	-5.12	265.49*
	(385.05)	(82.41)
Number of Payments ***x*** CFPL Passage thru Start	1,184.92**	6.59
	(416.64)	(89.17)
Number of Payments ***x*** CFPL Passage thru Start ***x*** CA	672.46	-52.56
	(1,056.40)	(226.10)
Number of Payments ***x*** After CFPL	312.74	-131.49*
	(189.35)	(40.53)
Number of Payments ***x*** After CFPL ***x*** CA	-1,564.55*	-238.35*
	(473.82)	(101.41)
CFPL Passage thru Start	8,915.88*	-612.16
	(3,005.94)	(643.36)
CFPL Passage thru Start ***x*** CA	4,197.81	20.26
	(6,896.64)	(1,476.08)
After CFPL	-2,789.38	-79.74
	(1,426.63)	(305.34)
After CFPL ***x*** CA	815.52	1,782.93*
	(2,790.18)	(597.18)
CA FE	5,805.70	5,850.71
	(71,330.24)	(15,266.69)
Constant	-21,790.70	-8,814.60*
	(1.77)	(3.34)
Other Controls	X	X
Zip 3 FE	X	X
Servicer FE	X	X
Origination Year FE	X	X
Delinquency Year FE	X	X
Property Type FE	X	X
Loan Purpose FE	X	X
Adj. R2	0.74	0.28
Observations	26,187	

Notes: The estimates above are based on the estimation of a model studying costs and revenues of foreclosure sales. The dependent variables in the models are the revenues or costs from the foreclosure sale. The sample is restricted to loans in sand states or Arizona, California, Florida, and Nevada. Model 10.1 includes foreclosures in the near term before and after the CFPL law or between January 2008 and July 2009 and those between January 2011 and June 2012. The same fixed effects capturing different time periods surrounding the Delay Law are used with results relative to the period before the CFPL law was passed. The same control variables used in prior models are included but not reported. Standard errors are in parentheses. *-Indicates significance at a 5% threshold.

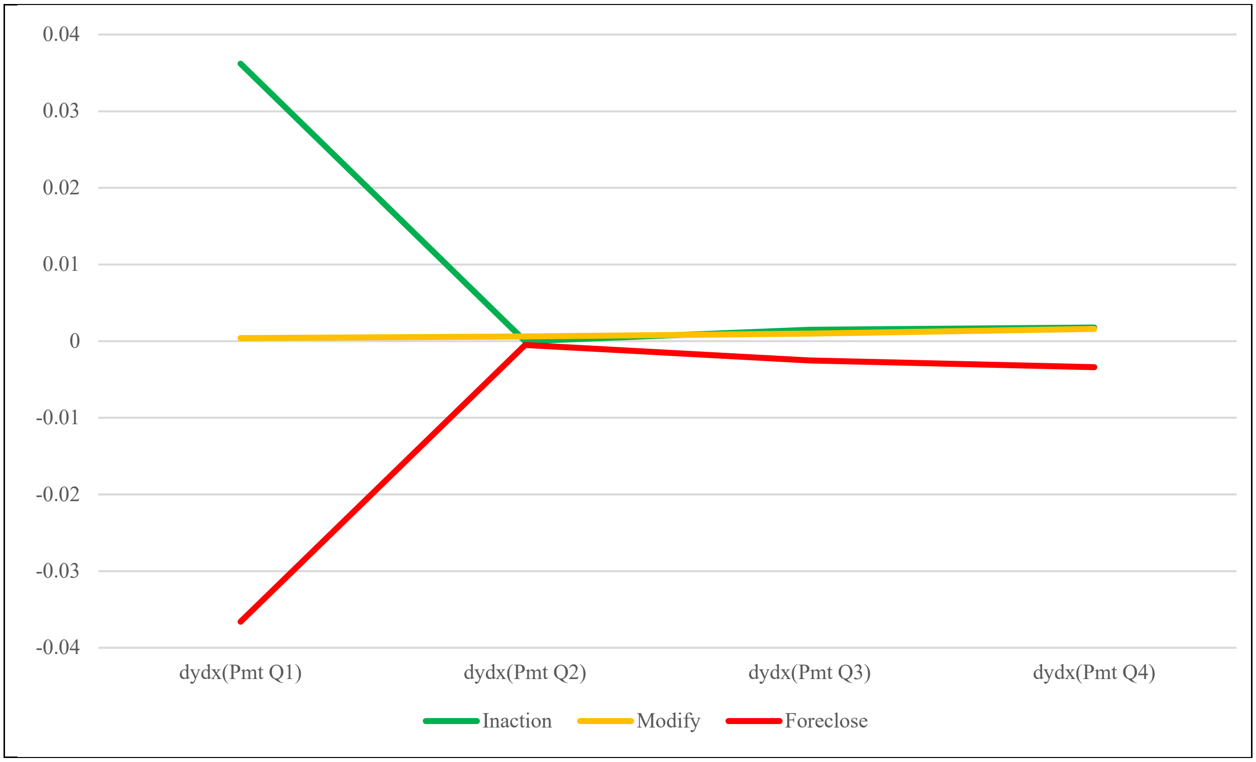
Exhibit B: Figures

Figure 1: Graph of Mean Payments over time



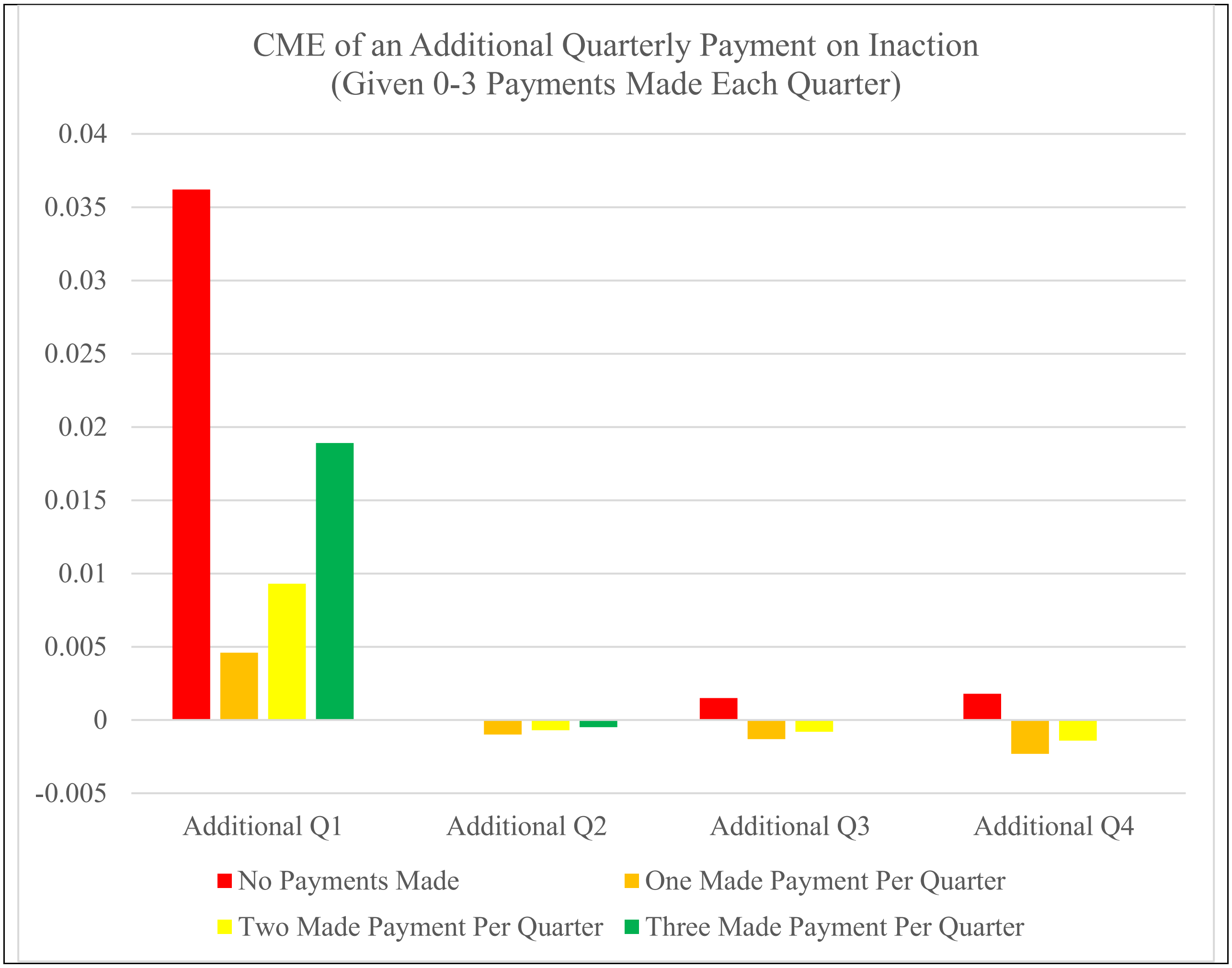
Notes: The above Graph represents the mean number of payments made while delinquent each year. The solid line indicates all delinquent loans while the dashed line is the mean payments only for loans that made a payment after first delinquency.

Figure 2: CME of a Payment Assuming Borrower Made No Payments



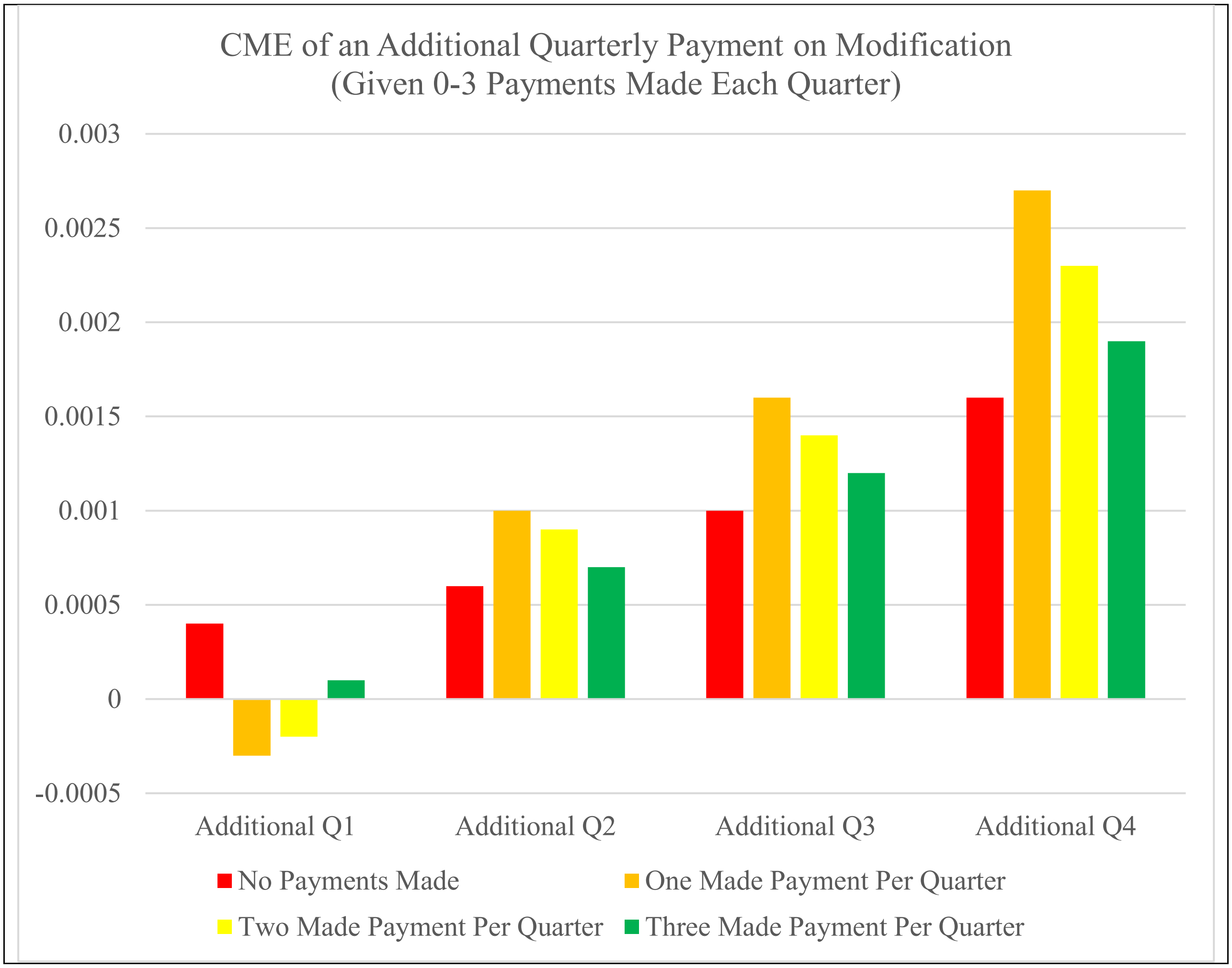
Note: The above figure represents conditional marginal effects of making a payment when the borrower made no payments over the past 12 months.

Figure 3: Conditional Marginal Effects of an Additional Payment on Inaction



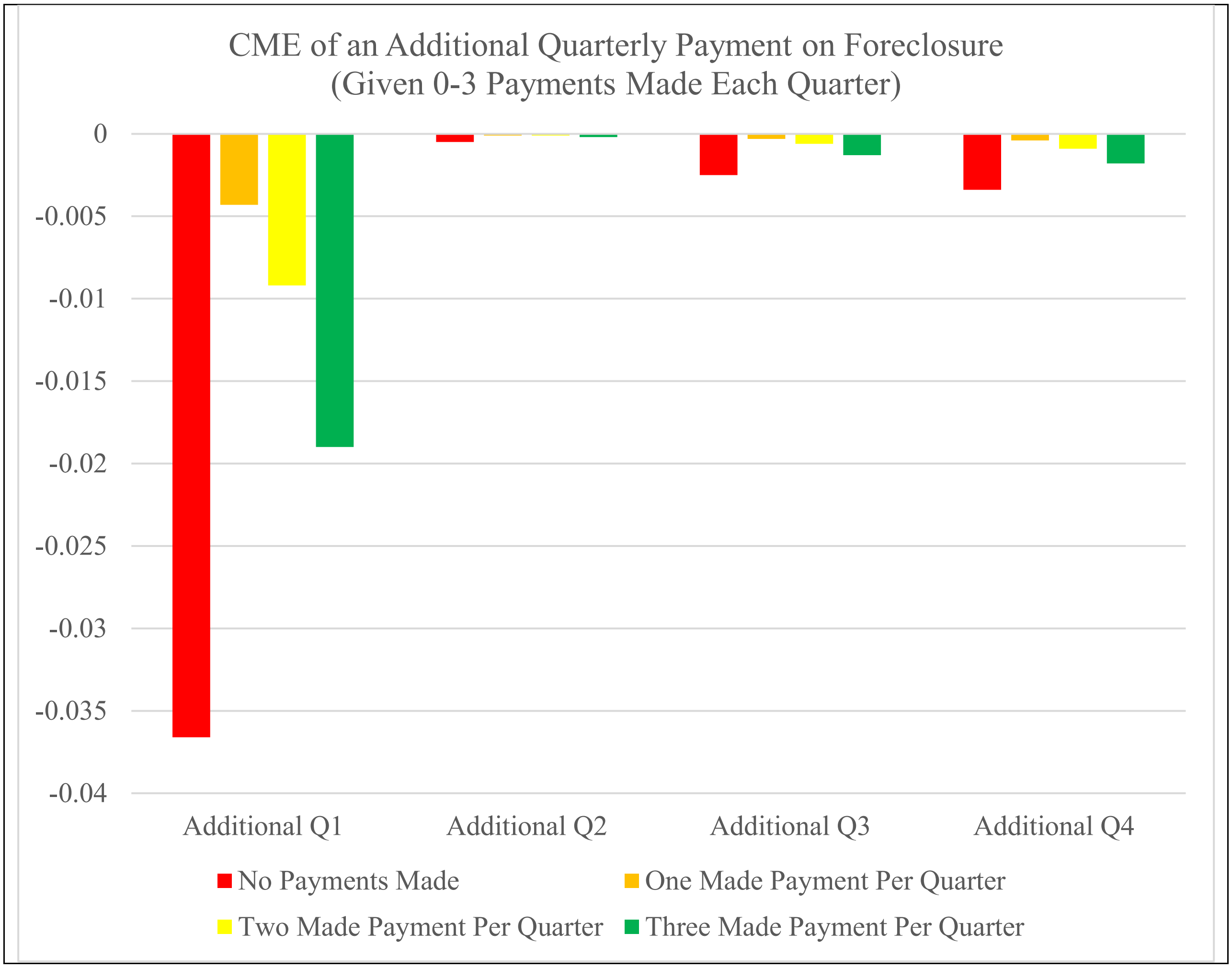
Note: The above figure represents conditional marginal effects of payments on inaction from Model 2.3. Each bar represents CMEs assuming the borrower made 0-3 payments in each quarter. Each set of bars represents the conditional marginal effect of an additional payment in a quarter given the varying amounts of payments made already.

Figure 4: Conditional Marginal Effects of an Additional Payment on Modification



Note: The above figure represents conditional marginal effects of payments on modification from Model 2.3. Each bar represents CMEs assuming the borrower made 0-3 payments in each quarter. Each set of bars represents the conditional marginal effect of an additional payment in a quarter given the varying amounts of payments made already.

Figure 5: Conditional Marginal Effects of an Additional Payment on Foreclosure



Note: The above figure represents conditional marginal effects of payments on foreclosure from Model 2.3. Each bar represents CMEs assuming the borrower made 0-3 payments in each quarter. Each set of bars represents the conditional marginal effect of an additional payment in a quarter given the varying amounts of payments made already.

Appendix

Table A1: Summary Statistics and Tests of Balance of the Matched Samples

	No Payments After Default		Payments After Default		Tests of Balance	
	Mean	Std. Dev.	Mean	Std. Dev.	Std. Diff. of Means	Ratio of Var.
FNMA Loans in MSA	2.14	1.21	1.93	1.11	0.18	1.09
Origination Amount	2.41	1.18	2.22	0.96	0.18	1.23
Current LTV	89.38	28.36	90.74	29.36	-0.05	0.97
Credit Score	670.48	62.92	672.99	54.18	-0.04	1.16
Mortgage Insurance FE	24.93	43.26	25.56	43.62	-0.01	0.99
Change in Case Shiller	0.85	0.22	0.86	0.23	-0.04	0.96
Change in Mortgage Rate	0.71	0.17	0.72	0.12	-0.07	1.42
Time Since 1st Default (Mo)	10.14	3.54	9.63	3.29	0.15	1.08
Number of Loans	162,364		162,364			
Monthly Loan Observations	2,113,953		4,094,330			

Notes: This table presents summary statistics and tests of balance for a matched sample drawn from a sample 90+ day delinquent Fannie Mae loans. A propensity score matching process matches borrowers that made payments after first default with borrowers which did not. Matches are limited to loans in the same Zip 3 and within 12 months of first default. Time varying traits are taken at first default.

The standardized difference of the mean and the ratio of the variance are used for matching balance diagnosis following the matching literature (Rubin, 2001; Austin, 2011). Following Rubin (2000), a variable is well balanced if and only if the standardized difference of means falls in the range of (-0.25, 0.25), and the ratio of the variance falls in the range of (0.5, 2). All covariates balance according to this criterion.