Why Don't Lenders Renegotiate More Home Mortgages? Redefaults, Self-Cures and Securitization
ONLINE APPENDIX

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I. Identifying Modifications in the LPS Dataset

In this section we discuss in detail the assumptions that we used to identify modified loans in the LPS dataset. The LPS dataset is updated on a monthly basis. The updated data include both new mortgages originated and a snapshot of the current terms and delinquency status of outstanding mortgages. For a given mortgage, we compare the updated terms to the terms at origination, as well as to the terms from the preceding month; if there is a material change over and above the changes stipulated in the mortgage contract, we assume that the contract terms of the mortgage have been modified.

A. Interest-Rate Reductions

We use different sets of rules to identify reduced interest rates for fixed-rate mortgages (FRMs) and adjustable-rate mortgages (ARMs). In principle, identifying a rate change for an FRM should be easy because by definition the rate is fixed for the term of the mortgage. However, after a detailed inspection of the LPS data it became apparent that some smaller rate fluctuations were likely due to measurement error rather than to an explicit modification. Thus, we adopt a slightly more complex criterion, which requires that *all* of the following conditions are met: the difference between the rate at origination and the current rate must be greater than 50 basis points; the difference between the rate in the previous month and the current rate must be greater than 50 basis points; either the mortgage must be 30 days delinquent with the loan currently in loss mitigation proceedings (as reported by the servicer) or the difference between the rate in the previous month and the current rate must be greater than 300 basis points. The final condition allows for the possibility that a loan that is current could feasibly qualify for a modification.

Identifying interest-rate reductions for ARMs is slightly more complicated because by definition the interest rate is variable and can move both up and down. The LPS data contain the information necessary to figure out how much the interest rate should move from month to month. This calculated rate is often referred to as the "fully indexed rate," since it is normally specified as a fixed spread above a common nominal interest rate (the "index"). The LPS dataset contains information regarding the initial rate, the appropriate index, and the spread between the index and the mortgage rate. In addition, the majority of ARMs are characterized by a period at the beginning of the contract in which the interest rate is held constant (these mortgages are often referred to as hybrid ARMs). At the end of this period, the interest rate adjusts (or "resets") to a certain spread above an index rate and then subsequently adjusts at a specific frequency. The LPS dataset also contains information regarding the length of the initial fixed period, enabling us to identify this period in the data and determine the point at which the interest rate should begin to adjust (we refer to this point as the reset date). Our criterion for identifying an interest-rate reduction for an ARM requires that *all* of the following conditions are met: the difference between the rate at origination and the current rate must be greater than 50 basis points; the difference between the rate in the previous month and the current rate must be greater than 50 basis points; if the reset date has passed, then the difference between the fully-indexed rate and the current rate must be at least 100 basis points; either the mortgage must be 30 days delinquent with the loan currently in loss mitigation proceedings (as reported by the servicer) or the difference between the rate in the previous month and the current rate must be greater than 300 basis points. The final condition which allows for the possibility that a loan that is current could feasibly qualify for a modification. Modest month-to-month decreases in the interest rate (of 200–300 basis points) also qualify as interest-rate reductions if the loan is reported to be less delinquent. Our inspection of the data suggests that the majority of modifications involve resetting the delinquency status back to current, or to minor delinquency, so conditioning on this change likely eliminates many false positives.

B. Term Extensions

In theory, it should be straightforward to identify term extensions in the LPS data, but it can be tricky to do so because of possible measurement error in the variable that measures the remaining loan term. We define a term extension in the LPS dataset to be a case in which the loan was at least 30 days delinquent at some point and the remaining term increases by more than 19 months *or* more than the difference between the original term of the loan and the remaining term (for example, if the original maturity is 360 months and the loan has 350 months remaining, then the increase in length must be at least 11 months); we also require that either the monthly payment decreases, the principal balance increases, or the loan is in loss mitigation.

C. Principal-Balance Reductions

A reduction in the remaining balance of a mortgage is perhaps the most difficult type of modification to identify, because of the prevalence of "curtailment" or partial prepayment among borrowers. For example, it is common for borrowers to submit extra mortgage payments in order to pay down the loan at a faster rate. For this reason, we were forced to adopt strict criteria to limit the number of false positives. Our criterion for identifying a principal-balance reduction requires that *all* of the following conditions are met: the month-to-month decrease in the remaining principal balance must be at most -10 percent and cannot be less than -30 percent (the upper bound does not matter as much as the lower bound—we experimented with -40 and -50 percent but did not find a substantial difference); the principal balance recorded in the previous month must be greater than \$25,000 (since we look only at first-lien mortgages originated after 2004, this cutoff does not bind often); the month-to-month payment change must be negative (there are only a few cases in which the principal balance is reduced without a corresponding decrease in the payment—in these cases the term is extended and thus the modification is designated as a term extension); the mortgage must be either 30 days delinquent or currently in loss-mitigation proceedings (as reported by the servicer).

D. Principal-Balance Increases

For interest-only and fully-amortizing mortgages, identifying an increase in the principal balance due to the addition of arrears is relatively straightforward; it is trickier for mortgages that allow for negative amortization, because by definition the principal balance is allowed to increase over the course of the contract. Our criterion for interest-only and fully-amortizing mortgages requires that *all* of the following conditions are met: the month-to-month principal balance must increase by at least 0.5 percent (to rule out measurement error in the data); the loan must have been at least 30 days delinquent at the time of the balance increase; the month-to-month payment change must be positive, unless there is also a corresponding increase in the term of the loan. For mortgages that allow for negative amortization, the criterion is similar but the balance increase must be at least 1 percent and there must be a positive change in the delinquency status of the loan.

E. Potential Sources of Error

Contract change algorithms are not perfect and there are two realistic situations where contract-change algorithms are likely to make errors. The first is principal forbearance where algorithms will generally report much larger modifications than actually occur. In a principal forbearance modification, the lender reduces the balance on the loan by \$X and then creates a new second mortgage for \$X that is due on sale or at the time of refinance, but on which the borrower makes no payments. The algorithm used in this paper will pick up the reduction in the balance of the original loan but will fail to identify the existence of the newly created second mortgage. Generally, principal forbearance was widely used only in GSE loans, and even then only later in the sample, so we do not view this as a major problem.

The second problematic situation is interest rate freezes on subprime adjustable-rate mortgages (ARMs), where contract-change algorithms will fail to report modifications when, in fact, they have occurred. The issue here is that the dramatic decline in LIBOR and other indexes used to determine rates on ARMs during the crisis period had the consequence of freezing the interest rate on most subprime ARMs regardless of whether the lender changed the contract. In general, we do not view this as critical to the results since the reason the algorithm fails to identify the modification is precisely because it does not really benefit the borrower. In addition, one could argue that since the only benefit of subprime ARM rate freezes occurs in the distant future when policy makers raise short-term interest rates, one should not identify rate freezes as modifications at all.

F. Tweaking the Algorithm

In the paper we arrived at our modification algorithm by minimizing the false positive and false negative rates as measured using the CTSLink data that we describe in the text. Thus, the algorithm reflects the best combination of parameters we could find with the objective being to minimize both the false positive and false negative rates. While we believe this is a natural way of choosing algorithm parameters, we also want to ensure that the main results in the paper are not highly sensitive to small changes in the algorithm. As a robustness check, we decided to change the parameters of the algorithm in such a way as to decrease the number of false negatives at the expense of increasing the number of false positives. Our rationale for choosing this particular change is that our baseline algorithm makes sense if false negatives and false positives are equally bad. However, one could argue that false negatives are worse because we may be systematically missing important modifications. In particular we may be missing a type of modification that is more common for portfolio versus securitized loans, which could serve to bias our regressions toward finding small differences in modification rates. Below are the changes we made to the algorithm, as well as the impact of these changes on the performance of the algorithm on the Wells Fargo dataset.

- We changed the fixed-rate mortgage rate reduction threshold to 0 basis points from 50 basis points (i.e. we flag a modification when we observe any reduction in interest rate instead of just flagging one when the reduction is greater than 50 basis points).
  - Percentage of false positives 10.3% (before it was 8%). 46% of new modifications identified are false positives.
- We changed the adjustable-rate mortgage rate reduction threshold to 0 basis points from 50 basis points (i.e. we flag a modification when we observe any reduction in

interest rate instead of just flagging one when the reduction is greater than 50 basis points; the other thresholds for flagging modifications for ARM loans remain).

  - Percentage of false positives 24.6% (before it was 22%). 70% of new modifications identified are false positives.

- We changed the minimum increase in principal balance to 0.1% from 0.5% (i.e. we flag a modification when we observe an increase in principal balance that is greater than 0.1% of the remaining balance instead of just flagging one when the increase is greater than 0.5%).

  - Percentage of false positives 12.7% (before it was 12.4%). 29% of new modifications identified are false positives,

Overall false positives using the changed algorithm increased to 18.7% (compared to 16.9% with the optimized algorithm). Overall false negatives using the changed algorithm decreased to 16.3% (compared to 17.2% with the optimized algorithm). Table I shows how theresults (panels A and B of Table IV in the paper) change when we re-estimate our main specification using the new algorithm that includes the changes described above. We find that changing the algorithm in this way does not significantly alter the qualitative or quantitative magnitudes of our main results.

In addition to tweaking our algorithm on the CTSLink data, we also calculated a set of alternative false positive and false negative rates by applying the algorithm to a much more representative mortgage dataset. We recently obtained access to Corelogic data, which is a loan-level dataset on non-agency, privately securitized mortgages, and is much more representative of the PLS market compared to CTSLink. The Corelogic dataset also contains flags for servicer reported modifications, and thus we were able to calculate false positive and false negative rates using these data. We find a very similar false positive rate (around 19 percent), and a significantly lower false negative rate (around 10%).

Table I
Results with Changes to the Modification Algorithm

Panel A: Concessionary Modifications					
	All Loans	Subprime	FICO < 620	Non-miss Doc and DTI	Full Doc
Portfolio Mean	0.014	0.015	0.014	0.011	0.01
PLS Mean	0.026	0.028	0.031	0.026	0.030
PLS Mg. Eff. (Logit)	0.011***	0.01*	0.014**	0.014**	0.019**
	(3.04)	(1.71)	(2.03)	(2.60)	(2.49)

Panel B: All Modifications					
	All Loans	Subprime	FICO < 620	Non-miss Doc and DTI	Full Doc
Portfolio Mean	0.117	0.096	0.119	0.118	0.115
PLS Mean	0.109	0.116	0.13	0.116	0.126
PLS Mg. Eff. (Logit)	0.003	0.014	0.014	0.010	0.020*
	(0.62)	(1.5)	(1.37)	(1.32)	(1.92)
# Mortgages	445,431	206,752	177,491	246,398	174,375

Notes: *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. The first two rows of each panel refer to portfolio and PLS unconditional probabilities of modification in each sample; the third row in each panel shows marginal effects computed from logit models with a 12-month horizon that include all the controls described in Table III in the text; t-statistics are reported below the marginal effects. Standard errors are clustered at the zip code level. The dependent variables follow the same definitions as those in Table III in the text. "PLS" is an indicator variable for whether the loan was privately securitized (as opposed to being on a bank's balance sheet) at the time that it became 60 days delinquent. The first set of results in all three panels includes all loans, the second set has only subprime loans, the third set includes only loans with a credit score below 620, the fourth set has observations where debt-to-income and documentation status are non-missing in the data, and the last column in each panel includes only loans that have full documentation; each set includes only loans that have become 60 days delinquent.

II. Results by Sample Period

Table II
Results by Sample Period

Panel A: Concessionary Modifications

	Early Sample	Middle Sample	Late Sample
PLS Mg. Eff. (Logit)	0.001	-0.023***	-0.041***
	(0.85)	(23.98)	(39.83)
GSE Mg. Eff. (Logit)	0.002***	-0.003**	0.013***
	(2.81)	(2.02)	(12.25)
PLS (Hazard Ratio)	0.885***	0.595***	0.695***
	(5.84)	(45.92)	(41.36)
GSE (Hazard Ratio)	1.117***	0.497***	1.369***
	(4.44)	(54.49)	(40.67)

Panel B: All Modifications

	Early Sample	Middle Sample	Late Sample
PLS Mg. Eff. (Logit)	0.006***	-0.014***	-0.038***
	(4.37)	(9.84)	(35.98)
GSE Mg. Eff. (Logit)	-0.004**	-0.043***	0.003***
	(2.50)	(33.92)	(3.08)
PLS (Hazard Ratio)	1.029**	0.733***	0.677***
	(2.37)	(31.72)	(45.79)
GSE (Hazard Ratio)	0.820***	0.383***	1.288***
	(14.75)	(88.04)	(34.35)

Panel A: Cures

	Early Sample	Middle Sample	Late Sample
PLS Mg. Eff. (Logit)	0.018***	-0.039***	-0.031***
	(6.83)	(14.75)	(20.88)
GSE Mg. Eff. (Logit)	0.077***	0.020***	0.011***
	(27.38)	(7.24)	(8.17)
PLS (Hazard Ratio)	0.959***	0.869***	0.879***
	(8.56)	(24.16)	(25.47)
GSE (Hazard Ratio)	1.104***	0.923***	1.122***
	(19.45)	(14.59)	(26.57)

Notes: *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. This table presents estimation results from logit modification regressions with a 12-month horizon and Cox proportional hazard models using data from three different periods. The "early sample" period corresponds to the main period of focus in the paper: modifications that occurred through the third quarter of 2008. The "middle sample" period corresponds to loans that were modified between the fourth quarter of 2008 and the second quarter of 2009. This period is very close to the period of analysis in **?**. The "late sample" period corresponds to loans that were modified between the third quarter of 2009 and February 2012.

III. Transferred Loans

There are loans that appear in the LPS data for which the servicing rights are later transferred to a servicer that does not report data to LPS. When these transfers occur, the loans drop out of the data and we do not observe their subsequent performance. While these loans only account for a small subsample of the data, they do not appear to be randomly selected. This is evident from a comparison with the non-transferred loans—both on their observable characteristics at origination and on their relative performance up until the time of transfer. In addition, a significantly higher percentage of portfolio loans are transferred than private-label loans. These observations imply that the sample of transferred loans cannot simply be dropped from the data, since doing so could result in a non-trivial bias of the estimated difference in cure and foreclosure rates between portfolio and private-label mortgages. In this appendix, we document some of the observable differences between transferred loans and non-transferred loans, we demonstrate the bias introduced in the cure-rate estimates when transferred loans are dropped from the data, and we discuss the appropriate way to deal with this sample of loans. As we explain below, dropping all of the transfers creates a large bias; alternatively, assuming that the transfers do not cure does not seem to create any bias.

Before we proceed, however, we should note that the appropriate way to deal with the issue of transferred loans is to estimate a hazard model rather than a discrete-choice model like a logit or probit. A hazard model appropriately accounts for right-censored observations and thus has the advantage of using observable information about the loans before they are transferred. All the results we obtain in the logit specifications are confirmed by the coefficients from hazard models we show in Tables **??**, **??**, and **??**. These results reinforce our conviction that the assumptions we are using for transfers do not introduce significant bias in the point estimates of the discrete-choice models.

In our sample, within 12 months of the date of the first 60-day delinquency, approximately 4 percent of private-label loans transfer while 6.5 percent of portfolio loans transfer. Table III displays the the mean and median FICO score and DTI ratio at origination for the samples of transferred and non-transferred loans. Mean and median FICO score is lower for transferred loans than for non-transferred loans, but the difference between portfolio transfers and non-transfers is much larger than the difference between private-label transfers and non-transfers. The same pattern emerges for DTI ratios.

In addition to transferred loans having worse observable characteristics, they also perform significantly worse before they are transferred than loans that are not transferred. Figure 1 displays the Kaplan–Meier cure hazards for the samples of transferred loans and of non-transferred loans.[1] It is clear from the figure that transferred loans cure significantly less frequently than loans that are not transferred.

In addition, Table IV shows that transfers perform significantly worse than non-transfers in the period immediately before they are transferred. The table compares the status of transferred loans in the month before transfer to the status of all loans in the first twelve months after origination. A much lower percentage of transferred loans are current and a much higher percentage are seriously delinquent or are in foreclosure. This is especially true of the portfolio transfers.

As a result of the differences in observed characteristics and performance, it is clear that the transferred loans cannot simply be excluded from the sample. Doing so would create a serious bias in comparing cure rates between portfolio and private-label loans. The bias introduced by removing transferred loans from the sample works to increase the cure-rate estimates for portfolio loans, since the portfolio loans that are transferred are of worse quality than the private-label loans that are transferred.

Instead of excluding transferred loans, we opt to keep these loans in the sample when we estimate the logit models for modifications and cure rates.[2] We then compare those estimates to the ones we obtain from hazard models for the same time periods and covariates. As we mentioned above, hazard models can account for the differences we observe in the data between transferred and non-transferred loans, so these models should mitigate most of the concerns we mention regarding those differences. We should point out, however, that hazard models cannot control for scenarios in which the transferred loans perform worse *after* they are transferred. An implicit assumption in a hazard model is that right-censored observations perform the same as non-censored observations after the former drop out of the data. Given that transferred loans perform worse while we observe them, it is likely that they perform worse after we stop observing them. As a result, a hazard model might still overstate cure rates for portfolio loans, suggesting that the true differences in cure rates between portfolio and private-label loans may be even smaller than those we present in Tables **??** and **??**.

[1] We define cures in the same way that we defined them in section III.D above; we assume in the figure that the cure state is absorbing.

[2] The issue of transferred loans is important when we compare our results to those obtained by **?**. These authors choose to exclude from their sample any mortgage that is transferred to a different servicer at any point during its life, which, as we point out above, artificially inflates the cure rate of seriously delinquent portfolio loans relative to the cure rate of private-label loans.

Table III
FICO and DTI Distribution: Transfers and Non-transfers

		Transfers			Non-transfers		
		#	Mean	Median	#	Mean	Median
FICO	Private-label	1,276	628	627	68,442	632	632
	Portfolio	708	622	620	9,793	652	654
	Total	1,984	626	624	78,235	634	634
DTI	Private-label	1,636	42	41	40,821	40	41
	Portfolio	457	39	41	7,913	35	36
	Total	2,093	42	41	48,734	39	40

Table IV
Status of Loan in Preceding Period: Transfers and All Loans

	Transfers		All Loans	
Status in Previous Month	Private-label	Portfolio	Private-label	Portfolio
30 days delinquent	7.1%	6.8%	8.6%	9.3%
60 days delinquent	23.0%	16.0%	12.9%	12.9%
90 days delinquent	20.8%	27.4%	20.9%	21.6%
Current	9.5%	7.5%	14.0%	23.1%
Foreclosure Proceedings	32.9%	39.3%	24.6%	20.6%
REO	6.6%	2.8%	16.6%	10.1%

Table V
Comparison to Agarwal et al. (2010)

	Our Calculations	Their Calculations
Estimated Marginal Effect	0.027***	0.024***
	(20.77)	(9.38)
# Mortgages	345,048	431,172

Notes: *** denotes statistical significance at the 1 percent level. This table presents estimation results from logit modification regressions with a 6-month horizon using the data sample of **?**. The sample consists of non-GSE, first-lien mortgages that were current as of 2007:Q4 and then became 60 days delinquent at some point in 2008. The table shows the estimated marginal effect associated with a portfolio-loan indicator on the decision to modify a delinquent loan within 6 months of the delinquency. Standard errors are clustered at the zip code level. t-statistics are reported in parentheses below the marginal effects. **?**'s estimates are from their Table 3, Panel A, column 6.

Figure 1. Kaplan–Meier Estimator for Cures: Transfers and Non-Transfers