Adverse Selection in Mortgage Markets: Fannie Mae Selling Default Risk

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Abstract

A key result in the theory of adverse selection states that asymmetric information between the seller and the buyer affects prices. This paper provides the first evidence of adverse selection in Credit Risk Transfer (CRT) markets. I document that Fannie Mae CRT securities are issued at a 20 basis points discount compared to private label ones. To verify the existence of the lemons problem I show that sold loans are riskier than those on portfolio. Also, loans undisclosed in their public data are riskier than those disclosed, suggesting adverse selection in reporting. Fannie Mae delays the sale of better quality mortgages, a form of signaling that has become obsolete in post-crisis private markets.

Keywords: Agency reform, credit risk transfers, adverse selection, bond prices.

JEL classification: G12, G14, D82

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1 Introduction

Adverse selection can precipitate a market breakdown when the seller has private information about the quality of the asset (Akerlof, 1970). Since the onset the financial crisis, policy makers and researchers have increasingly found this friction to be at work in mortgage markets, often in connection with the originate-to-distribute model (Ashcraft and Schuermann, 2008; Ashcraft, Gooriah, and Kermani, 2019; Beltran, Cordell, and Thomas, 2017) in the context of subprime and low documentation loans. But while it is now accepted that the sellers of such loans took advantage of superior information to securitize low quality mortgages (Keys, Mukherjee, Seru, and Vig, 2010; Nadauld and Sherlund, 2013), it is unclear whether post-crisis markets, composed primarily of conforming loans and dominated by the government-sponsored enterprises (GSEs), are affected by the same issue. Using novel data on Fannie Mae's Credit Risk Transfers, I provide evidence of adverse selection in mortgage markets and its effect on bond prices.

Historically, the GSEs have followed a buy-to-hold approach towards the default risk of their mortgages, which has grown to over $5.5 trillion (Federal Housing Finance Agency, 2019). Over a decade into the conservatorship, the US Congress is yet to return them to private ownership. Prompted by the FHFA's Strategic Plan to end Conservatorships (2012), the agencies designed a credit derivative to reduce their footprint in mortgage markets, known as Credit Risk Transfer (CRT). Through CRTs, they have sold the default risk on a portion of $2.8 trillion total unpaid balance.

Despite the growth of CRT penetration of the agencies' portfolio over the recent years, the fact that it remains far from 100% implies that they remain buy-to-hold investors in default risk. A buy-to-hold investor has special incentives to acquire information about the quality of her loans vis-à-vis one who buys to distribute (An, Deng, and Gabriel, 2011). I argue that this makes CRT markets relatively prone to adverse selection compared to private label ones. I formulate the lemons problem using the information economics model used by Adelino, Gerardi, and Hartman-Glaser (2019). Sellers have superior information about the quality of their loans. In equilibrium, the price reflects the severity of asymmetric information which, I argue, is worse in credit risk transfers due to the agencies' investment strategy. Because the CRT buyer understands the adverse selection problem, the equilibrium price of the buy-to-hold investors' assets reflects a lemons discount.

I document that Fannie Mae CRT tranches are issued at a discount relative to comparable private label securities. Using proprietary data on private label and CRT bond prices from Moody's ABSNet, I find that the spread at issuance of the latter is 24 bp higher (see Table 2). The pricing differential is robust to controlling for risk attributes at the bond level such as rating, detachment point and interest rate type, as well as deal level risk attributes like average FICO score and LTV ratio.

Because of the aggregate nature of the previous comparison, it is subject to differences in the underlying mortgages that are unaccounted for. Using a large sample of CRT and private label loans (also drawn from Moody's ABSNet) I run a second test that incorporate borrower and loan risk characteristics. Indeed, CRT coupon gap to Treasury is 20 bp higher than that of similar private label loans.

The results at the bond and loan level provide evidence that CRTs trade at a discount. Using the model, I interpret the pricing difference as a lemons discount related to the degree of asymmetric information, proxyed by the risk dispersion of the loans in the sellers' pool. In equilibrium, the lemons discount is increasing in this dispersion measure. Empirically, I show that the distribution of FICO scores of Fannie Mae's securitization shelf (CAS) is indeed more disperse than that of private label shelves, despite the fact that private loans have no a priori restriction on FICO scores while Fannie Mae are restricted to scores above 620. In light of the model, this is evidence that the magnitude of the lemons problem is indeed linked to the investment strategy.

However, the previous tests do not directly uncover the agency friction. To provide direct evidence of adverse selection, I use Fannie Mae data to compare portfolio loans to credit risk transfers. Although Fannie Mae provides the data freely, it does not flag CRT loans so that the quality differential is not observable to individual market participants. In order to identify the CRT status of a given loan, I match the public data on Fannie Mae loans to the ABSNet data. I find that CRT mortgages are riskier compared to portfolio.

The comparison between portfolio and CRT loans suggests that there is adverse selection in selling. I also argue that there is adverse selection in reporting. Because the CRT loans that Fannie Mae publicly disclose (without labeling them as CRT) are a subset of my ABSNet data, I can compare *disclosed* and *undisclosed* Fannie Mae loans. I show that the former, i.e. loans that I find in both samples, have lower 90 day default rates and LTV ratios than the latter (i.e. those I only find in the ABSNet data). The findings suggest Fannie Mae's public data are subject to reporting bias, which is consistent with the adverse selection hypothesis presented so far.

Besides pricing in a discount, the market exhibits a feature consistent with adverse selection, namely a signaling device. More specifically, risky mortgages tend to sell earlier. This constitutes a costly signal of quality and is thus credible (Fuchs and Skrzypacz, 2019). I observe such trading pattern in CRT markets. Similarly, Adelino et al. (2019) find evidence of this mechanism over the boom time period. The evidence I provide suggests that such a form of signaling default risk has become obsolete in private markets. Nevertheless, a simple extension of their theory adequately captures how current markets signal default and prepayment.

An alternative explanation is that mortgages that do not terminate soon after origination are simply of better quality. In that case, a longer time to sale would mechanically reflect better quality without any signaling motive. This rationale would apply to prepayment as well as to default. To argue that the mechanical relationship is insufficient as an explanation, I introduce a placebo test exploiting the fact that CRTs investors do not lose money when borrowers prepay. In the model, when investor cash flows are not affected by termination all seller types pool in equilibrium and no signaling takes place. Empirically I verify that the prepayment probability of CRT loans is unrelated to time to sale, but not for nonagency markets where investors buy both the default and the prepayment risk.[1] The results make the mechanical relationship unlikely, and instead support the adverse selection hypothesis.

The closest paper to mine is An et al. (2011). Their study of pre-crisis commercial MBS finds that conduit loans trade at a premium relative to portfolio loans. Their rationale is the one I posit, namely that a buy-to-hold strategy elicits asymmetric information and adverse selection. But unlike them, my loan level data allows me to compare portfolio and CRT loans to provide direct evidence of the adverse selection. Moreover, I provide evidence to their conjecture that a buy-to-hold strategy elicits a higher dispersion of loan quality across the pool.

More broadly, this paper contributes to a literature on adverse selection in mortgage markets, where the GSEs are portrayed as either inflicting adverse selection on the market (Downing, Jaffee, and Wallace, 2009) or suffering from it (Ambrose, LaCour-Little, and Sanders, 2004; Ouazad and Kahn, 2019). In particular, Ouazad and Kahn (2019) argue that more conforming loans are being issued in hurricane risk areas, thus transferring this risk from private agents to the GSEs. My findings suggest that the agencies use credit risk transfers to send the risk back to private markets. Mine is not the first paper to consider how CRTs respond to hurricane risk. Gete, Tsouderou, and Wachter (2020) identify the effect of hurricanes Harvey and Irma on secondary market prices, shedding further light on how capital markets price credit risk.

The paper proceeds as follows. Section 2 describes institutional details of the credit risk transfer mechanism. I describe the data in Section 3. Section 4 provides empirical tests for the two

[1] My sample does not exclude loans that had to be purchased back by the originator under early payment default (EPD) clauses. These early payment defaults were a concern in pre-crisis markets, especially among subprime mortgages (Mayer, Pence, and Sherlund, 2009). Adelino, Gerardi, and Willen (2014) find that, over the same time period, EPD is strongly correlated with the securitization status of a loan. I do not observe whether a given loan is covered by an EPD clause, but I expect that the presence of such loans reduces the incentives for signaling by delaying the transaction. Thus I expect my estimates to be a lower bound of the true parameter.

hypotheses, that of the pricing discount and that of adverse selection. Section 5 formulates the information economics model and lays out the placebo evidence of signaling. Section 6 concludes.

2 How credit risk transfers work

Fannie Mae and Freddie Mac have accumulated a residential mortgage portfolio of over $5.5 trillion. Mortgages are subject to both prepayment and default risk. Historically, the GSEs have transfered prepayment risk to agency MBS investors but retained default risk on their portfolio. To reduce their large and growing exposure, they have structured credit risk transfers on $2.8 trillion of outstanding loan balance (see Figure 6.2). This has reopened a market for default risk which had virtually disappeared with the collapse of private label securitization in 2007. Since its advent in 2013, CRT bond issuance has grown to over $60 billion.

I study Fannie Mae's Connecticut Avenue Securities (CAS), which composes the majority of credit risk transfers issued so far.[2] For a comprehensive discussion of CRT programs I refer the reader to Goodman (2018) and Finkelstein, Strzodka, and Vickery (2018). The key feature of CAS bonds is the linkage of the required principal payments to the default performance of a mortgage reference pool. In other words, the CRT bond is a credit derivative, allowing the GSEs to synthetically tranche the default risk exposure and sell it to a private investor.

Credit risk transfers are similar in structure to Collateralized Mortgage Obligations (CMOs). Both types of securities trade in secondary markets and both of them carry default risk. However, the former carries no prepayment risk while the latter does. Another important difference lies in typical tranche seniority. Credit Risk Transfers consist almost exclusively of mezzanine tranches, whereas a typical CMO tranche is senior.[3] The underlying assets also differ. CRT mortgages are

[2] A second form of risk transfer, front-end CRT, is done at the point of acquisition involves mortgage insurance prior to securitization and thus loans are of considerably lower seasoning. In some of these forms, the loan seller retains a portion of the credit risk. The GSEs have also used "deep cover" private mortgage insurance (PMI), whereby mortgage insurers assume more of the risk than what is strictly necessary to reach an overall loan to value (LTV) ratio of 80%.
A way to categorize CRT programs is by holder of the risk. Whereas STACR and CAS are traded in capital markets, other forms of credit risk transfer involve insurance and reinsurance: these are Freddie Mac's Agency Credit Insurance Structure (ACIS) program and Fannie Mae's Credit Insurance Risk Transfer (CIRT) program. These reinsurance transactions are structured the same way as STACR/CAS and are used to reinsure a stand-alone reference pool. In the case of ACIS, the reinsured asset is the retained vertical slice of mezzanine risk in a STACR transaction. Both ACIS and CIRT can be front-end or back-end.

[3] On one hand, senior tranches (which incur losses only when credit risk is above 400 basis points) are commonly perceived as catastrophe bonds (Coval, Jurek, and Stafford, 2009). Under the premise that the GSEs are the efficient holders of catastrophic risk these tranches should not be sold. On the other hand, holding the first loss piece (corresponding roughly to the first 50 basis points of pool losses) is see as an incentivize to the GSEs in the form of

conforming loans, which involves a size limit as well as a FICO score lower bound of 620. Moreover, their maximum LTV is bounded above by 80%. None of these restrictions apply to private label mortgages, which over time has featured subprime and low documentation loans. The differences documented so far motivate the controls I introduce to both bond level and loan level regressions.

Credit risk transfers were initially devised by the GSE regulator, the FHFA. Its "Strategic Plan for Enterprise Conservatorships", introduced in 2012, was designed to reduce the GSEs' footprint in the mortgage market and shift some of the default risk towards the private sector (Goodman, 2018). From program inception, the reference pool of loans has grown over time to more than 60% as a proportion of single-family acquisitions. As Figure 6.1 shows, the share of CRT in Fannie Mae's portfolio has risen from an initial 41% to 65% in 2017. However, it remains far from the totality of the portfolio. Because Fannie Mae keeps a non-negligible share of the loans it buys, I argue it fits the description of a buy-to-hold investor.

3 Data

The main source is proprietary data from Moody's ABSNet, which tracks origination and performance for private label loans and the securities backed by them. ABSNet provides origination and performance data for over 90% of private label (PL) mortgages and mortgage-backed securities, including credit risk transfers.

For the bond level analysis, I start with the sample of collateralized mortgage obligations provided by Moody's ABSNet, which covers CRT deals. I drop 2,002 PL tranches that pay weighted average coupon (WAC) because CAS tranches pay based on either LIBOR or a fixed coupon. I then drop 810 A-rated tranches, which apply to senior tranches only and not to any Fannie Mae CRT (they are either unrated or rated Baa3 and below). The data cleaning yields a sample of 1,290 PL and 791 CRT bonds that I use for estimation. For each bond I compute the average FICO score and LTV of all the loans backing the pool.

The bond level data is summarized in Table 1. I observe that Fannie Mae CAS bonds exhibit an average yield spread at issuance of 1.17%, compared to 0.34% for private label securities. Another important difference lies in the detachment point, which on average is higher for PL bonds. Even after excluding A tranches, CRTs are placed at a lower position along the waterfall compared

skin in the game. The size of this first loss piece roughly corresponds to expected losses, so that mezzanine tranche risk carries mostly unexpected losses. See Finkelstein et al. (2018).

to private label bonds. Accordingly, my regressions at the bond level control for tranche level covariates such as the detachment point and the initial tranche rating.

For the loan level analysis, I start with a sample from the ABSNet containing 4.8 million CRT and 0.7 million private label loans, which I summarize in Table 3. CRT loans exhibit significantly lower seasoning, higher FICO scores and lower LTV ratios than private label loans. Delinquency rates are accordingly lower than those of private label loans. However, the coupon gap, computed as the difference between the interest rate at origination and the 10 year constant maturity Treasury on that date, is higher. To make loan types comparable across samples I keep only single family, first lien, 30-year fixed rate mortgages. I discard loans with FICO score lower than 620. Finally, I discard mortgages with loan balance at origination below $30,000 or above $1,000,000.

The outcome of the data cleaning process is a sample of 211,904 private label and 4,787,600 CRT loans, described in Table 4. The coupon gap, loan size and share of loans that are conforming by size are now similar. Some differences remain in the risk of private label and CRT loan types. Fannie Mae CRT still exhibit lower 90-day delinquency rates, though comparable LTV ratios and FICO scores.[4] Private mortgage insurance is more prevalent among CRT loans, as would be expected given that the agencies' hard requirement of an 80% LTV does not apply to private label mortgages.

Instead the seasoning of private label loans remains significantly higher, reflecting that several (post-2012) private label securities are built on loans originated as far back as the 1990s. See Figure 6.4. Because seasoning is one of the main variables of interest in this paper, I don't discard *legacy* loans (those already existing when CRTs began in 2013), but make it a control for it in my regressions.

To assess the presence of adverse selection, I compare the loans kept by Fannie Mae to the ones that were sold into CRTs using a large public sample of their loan purchases. I use 12.7 million loans, described in Table 7, which I downloaded from Fannie Mae's website on June 2019. Importantly, this version of the public Fannie Mae data does not distinguish CRT loans. To construct a flag, I match the two loan level samples. Given that ABSNet provides the near universe of privately sold loans, loans sold by Fannie Mae through CRT are present in this sample.

I match loans across datasets based on a combination of characteristics: seller name, credit score (FICO), loan to value (LTV) ratio, loan amount, metropolitan statistical area of the property (MSA) and date of origination (year-month). Of the 12.8 million loans in the initial Fannie Mae data, the combination of the above mentioned attributes identifies the loans almost uniquely (except

[4] I treat LTV observations on the combined sample by taking the minimum between loan LTV and borrower combined LTV, to treat erroneous data points.

for 0.45% of observations). As for the ABSNet data, the identification is unambiguous except for 2.73% of observations (see Table 6). To validate the match I compare attributes that were not matched on. For instance, I use a sample of debt to income ratios from both datasets and look at the distribution of differences. Over 99.9% of observations are within plus or minus one percentage point. While this might indicate different rounding across datasets, it validates the matching process. By keeping only observations uniquely identified by seller name, FICO, LTV, amount, MSA and origination year-month, I can merge the two datasets on the characteristics mentioned.

The merge yields an overlap of 1,369,815 observations. All of these data points do indeed carry a CRT label in the ABSNet data, so that the overlapping observations are a subset of the 4.7 million provided in the latter. I label the observations in the intersection of the two sets as "disclosed" CRT loans, i.e. I can find them in the public data. I call the rest of CRT loans (listed in the ABSNet but not in the Fannie Mae data) "undisclosed" CRT, and use this classification to understand adverse selection on reporting.

Applying the same cleaning steps I have described above to the Fannie Mae data, I obtain 7.6 million portfolio and 1.3 million CRT loans, summarized in Table 8. It shows that CRTs have slightly higher LTV ratios, but comparable FICO scores and default rates (but lower prepayment rates). In order to understand the pricing of CRT relative to private label loans, controlling for risk observables, I will now write regression models to provide evidence of a pricing gap.

4 Empirical results

I first test whether Fannie Mae CRT bonds are issued at a discount relative to private label securities. I estimate a linear regression of bond spreads on a CRT indicator as follows:

$$Spread_i = \alpha + \beta \mathbb{1}_{(i \in CRT)} + \gamma_i X_i + \gamma_d X_{d(i)} + \eta_{d(i)} \varepsilon_i \tag{1}$$

I estimate regression (1) on the sample of private label and Fannie Mae CRT securities described in Table 1, so that $\mathbb{1}_{(i \in CRT)}$ takes the value 1 if bond i is a CRT, and 0 if private label security. A vector X_i represents bond features at origination such as the detachment point (which indicates the position in the cash flow waterfall of the given tranche) and the Moody's rating. A vector of deal level covariates $X_{d(i)}$ includes average LTV and average FICO score. Finally, $\eta_{d(i)}$ represent year fixed effects. Table 2 records the results, which suggest CRT tranches are issued at a spread 24 bp higher than that of private label securities.

Although the results above control for deal level measures of average risk, there are other differences across collateral pools that I can better control for using a loan level test. I estimate the following specification:

$$Coupon\ gap_k = \alpha + \beta \mathbb{1}_{(k \in CRT)} + \gamma X_k + \varepsilon_k \tag{2}$$

I estimate regression (2) on the sample of private label and Fannie Mae CRT securities described in Table 4, so that $\mathbb{1}_{(k \in CRT)}$ takes the value 1 if loan k is a CRT, and 0 if private label. Loan level controls include FICO score, LTV and indicator for refinance mortgage. The comparison of CRT to private label loans, summarized in Table 5, suggest a coupon gap of 20 bp. In Section 5, I will rationalize this observation as a lemons discount. Like An et al. (2011), Result 1 will argue accordingly that the transaction price is decreasing in the severity of adverse selection.

So far, I have argued the price of CRT securities reflects a lemons discount. To explore directly whether adverse selection is at work, I take advantage of the fact that the sample matching I describe in Section 3 allows me to distinguish CRT loans within the public Fannie Mae data, something individual market participants are unable to do. This enables me to estimate a following linear probability model as follows:

$$\mathbb{1}_{(k \in CRT)} = \alpha + \gamma X_k + \varepsilon_k \tag{3}$$

The results of running regression 3 on the (matched) Fannie Mae data are provided in Table 9, which compares observable features of loans that Fannie Mae sold to those it kept on balance. Univariate tests suggest lower FICO scores are more likely to be sold through CRT. Similarly, higher LTVs, higher debt to income ratios, higher exposure to hurricanes and higher default risk loans are more likely to be sold than kept on balance.[5] Note that in the multivariate test, the coefficient sign flips for LTV and DTI. These values being endogenous to the FICO score due to the loan origination process, it does not controvert the interpretation that follows from the univariate tests.

While Fannie Mae reports just under 800,000 CRT loans in its public dataset (though without identifying them) the ABSNet sample shows there are over 2.8 million of them. As discussed before, the former set is contained in the latter. I call "disclosed" CRT loans those that appear on the public data (though without a CRT flag, as discussed before). Consequently, "undisclosed" mortgages are the ones present in the ABSNet supersample but not in the public sample. As Figure 6.12 shows,

[5] I define a hurricane risk county as a coastal county in one of the following states: FL, TX, NC, LA, SC, AL, GA, MI, NY and MA.

loans disclosed publicly on the website have higher FICO scores and lower default rates than those kept undisclosed. Regarding hurricane risk, the breakdown of Figure 6.9 shows a contrast. While disclosed loans exhibit a decreasing trend from 2014 onwards, the undisclosed loans show an upward trend during the same time period. The pattern of missing data suggests a reporting bias which is consistent with the adverse selection hypothesis.

5 An information economics model

I write a straightfoward extension of Adelino et al. (2019) to shed light on how incentives determine the type of signaling that takes place in equilibrium. First, I show that higher severity of asymmetric information (proxyed in the model by dispersion of loan riskiness) affects the equilibrium price. Then, I point out that when termination does not affect cash flows, a pooling equilibrium takes place where no signaling occurs. This motivates the empirical finding that there is no skimming for prepayments in CRT.

Time is infinite and continuous. At time $t = 0$, an originator purchases a mortgage for potential resale. This mortgage produces a cash flow of c dollars per unit of time until it terminates (by either default or prepayment) at some random time τ. The default (prepayment) time τ is an exponential random variable with parameter $\lambda > 0$, distributed on the compact interval $[\lambda_l, \lambda_l + \phi]$ according to the continuous density $f(\lambda)$. Both the mortgage originator and the competitive set of buyers are risk neutral. The seller and buyer discount cash flows at rates γ and r respectively, where $\gamma < r$. In the case where termination happens by default, the value of the mortgage for the seller is

$$\begin{aligned} U^d(\lambda, t, p) &= E\left[\int_0^t e^{-\gamma s}\mathbb{1}_{(s\leq\tau)}c\,ds + e^{-\gamma t}\mathbb{1}_{(t\leq\tau)}p \,|\, \lambda\right] && (4) \\ &= \frac{c}{\gamma+\lambda}(1 - e^{-(\gamma+\lambda)t}) + e^{-(\gamma+\lambda)t}p. && (5) \end{aligned}$$

Investors are price takers and take price $P^d(t)$ as given. Their value for a mortgage is given by their beliefs about the type they are facing:

$$p^d = E\left[\int_t^\infty e^{-r(s-t)}\mathbb{1}_{(s\leq\tau)}c\,ds \,|\, \lambda\right] = \frac{c}{r+\lambda} \qquad (6)$$

An equilibrium of the game is a pair of functions (T^d, P^d) where $T^d(\lambda)$ is the time at which a seller of type λ trades and $P^d(t)$ is the price at time t, such that:

1. Seller optimizes: $T^d(\lambda)$ solves $max_t U^d(\lambda, t, P(t))$ for each λ
2. Zero profit for investors: $P^d(T(\lambda)) = E\left[\frac{c}{r+\lambda(T^d)}|T^d(\lambda)\right]$.

An equilibrium is separating if $P^d(T(\lambda)) = \frac{c}{r+\lambda}$. If the price does not reveal the type, I say that the equilibrium is pooling. Adelino et al. (2019) solve for the separating equilibrium to show that:

$$T^d(\lambda) = \frac{log(r + \lambda_l + \phi) - log(r + \lambda)}{\gamma - r}. \tag{7}$$

Equation (7) establishes that the skimming property applies, namely that a separating equilibrium holds whereby T^d is decreasing in λ. To test this prediction, verified on pre-crisis data by Adelino et al. (2019), I estimate a linear probability model with either default or prepayment outcome indicator as the dependent variable and time to sale as the independent variable.

$$Outcome_{ijq} = \alpha + \beta_1 \text{Months to sale}_{ijq} + \gamma X_{ijq} + \gamma_q + \gamma_j + \varepsilon_{ijq} \tag{8}$$

In specification (8), i indexes the individual mortgage (CRT or private label), j indexes the state in which each mortgage is originated, and q denotes the year-quarter of origination. X_{ijq} is a vector of control variables including CRT indicator, FICO score, LTV ratio, loan amount and other loan covariates. The outcome variable is a dummy for either default (measured as whether a credit event took place) or prepayment. I use state and year-quarter (of origination) fixed effects, clustering standard errors at the same level. Months to sale is proxyed by the difference (in months) between the date of deal issuance (i.e. the securitization date) and the date when the loan was originated.

The results of estimating specification (8), with default as the outcome variable, are shown in Table 11. The fact that $\beta_1 < 0$ holds for CRT loans suggests that there is a negative and significant correlation between time to sale and probability of default in this market, as stated in equation (7). Adelino et al. (2019), who find evidence of such a relationship in subprime and low-doc markets, argue that this relationship indicates signaling. The results from Table 11 thus suggest that signaling takes place in credit risk transfers by delaying the sale of the mortgages.

To check whether a linear specification is sufficient, I examine the marginal effect of each month prior to sale. As Figure 6.8 shows, there is a negative and decreasing relationship between the month to sale and 90 day delinquency. When it comes to private label loans, no significant relationship between time to sale and default arise until the loan is very seasoned, i.e. only for legacy mortgages. The long term relationship between time to sale and loan quality would thus be better described by a non-monotonic function such as the one derived by Martel, Mirkin, and Waters (2019). For recent mortgages there is no statistically significant link, as seen before from the third column in Table 11. I interpret this as evidence that default risk signaling is at work in credit risk transfers but has become obsolete in private label markets.

To understand how adverse selection impacts equilibrium price, I substitute λ^d in equation 8 to recover the equilibrium price function in (9):

$$P^d(\lambda(t)) = \frac{c}{(r + \lambda_l + \phi)e^{-(\gamma - r)t}}. \tag{9}$$

This establishes the following result (previously proven by An et al. (2011)):

Result 1. $P^d(t)$ is decreasing in the severity of asymmetric information ϕ.

Result 1 states that the buyer internalizes the lemons problem, as in Akerlof (1970), leading to a pricing discount. An et al. (2011) argue that, regardless of the quality of the assets traded, a buy-to-hold strategy elicits more adverse selection concerns from the market than a buy-to-distribute one. I provide concrete empirical evidence in line with the quality dispersion effect highlighted by Result 1. As Figure 6.6 depicts, the distribution of FICO score finds the widest support for the CAS shelf, compared to private label ones. In line with this, Table 10 shows that both the interquartile range and the standard deviation of FICO scores is the largest compared to all other major private label shelves. In terms of the model, $\phi^{CRT} > \phi^{shelf}$ for any $shelf$ belonging to the private label. By Result 1, a lemon discount applies to CRT relative to private label shelves.

The findings reported in this section are based on performance after purchase, as defaulted mortgages do not belong in the same market segment. Thus, a potential alternative explanation for this relationship is that mortgages that do not terminate soon after origination are simply of better quality, regardless of private information. In that case a longer time to sale may mechanically reflect better quality rather than a signaling motive. This would be true both for termination by default and for termination by prepayment. In what follows I will use the theory to understand the effect of termination by prepayment. Then I will use a placebo test exploiting the fact that CRT investors are not concerned about prepayments to show that the mechanical relationship is insufficient as an explanation.

Using the theory, I show that investor incentives are necessary to elicit signaling. In particular, the type of termination (default or prepayment) affects whether the market equilibrium features a signaling device. Unlike default, prepayment does not affect the cashflows to the CRT investor. When cash flows are not affected by termination, the value function becomes:

$$
\begin{aligned}
U^p(\lambda, t, p) &= E\left[\int_0^t e^{-\gamma s} c\, ds + e^{-\gamma t} p \mid \lambda\right] && (10)\\
&= \frac{c}{\gamma}(1 - e^{-\gamma t}) + e^{-\gamma t} p. && (11)
\end{aligned}
$$

The first order condition for seller utility (11) yields

$$
p' = \gamma p - c.
$$

Now, I substitute the indifference condition for the investor

$$
P^p(t) = E\left[\int_t^\infty e^{-r(s-t)} c\, ds \mid \lambda_l\right] = \frac{c}{r}
$$

into the differential equation to obtain

$$
p' = (\gamma - r)p \tag{12}
$$

The general solution to equation (12) is of the form $p^p(t) = Be^{(\gamma - r)t}$. Thus the price is not affected by there is no equilibrium relationship between T^p and λ, i.e. a pooling equilibrium.

Proposition 1. When termination does not affect the asset cash flows, a pooling equilibrium follows.

Proposition 1 states that when cash flows are not affected by termination, there is no relationship between termination likelihood and time of sale. Importantly, this is what happens when a CRT loan prepays. In such a case, skimming does not happen because the termination event is irrelevant to investors, namely in CRT markets, but will take place in private markets where prepayment risk is borne by the investor.

The empirical results in Table 12 are consistent with this prediction. While longer time to sale is in general associated with lower prepayment probability, this is not the case for CRT loans. I interpret this as evidence that investors do not skim CRT markets for prepayments because it is unnecessary. This suggests that the relationship between termination and time to sale is not merely mechanical, because it reflects the investor's incentives.

6 Conclusion

Adverse selection can lead to a market breakdown when the seller has private information about the asset's quality. I show that Fannie Mae CRT securities face a pricing discount relative to private label bonds, as suggested by spreads at issuance that are over 20 bp higher. I argue that this issue is linked to the fact that Fannie Mae follow a buy to hold strategy with respect to default risk, despite the creation of the CRT market itself. This creates an incentive to acquire private information about the quality of the loans, which would not arise from a buy-to-distribute strategy. The lemons discount reflects investor concerns about adverse selection.

Though the pricing regressions do not identify the adverse selection channel, I compare Fannie Mae portfolio and CRT loans by taking advantage of novel data not observed by market participants. I show that loans sold are riskier than the loans retained by the GSE. The evidence suggests the agency's buy-to-hold strategy leads to private information and cherry-picking. These findings imply that a credible commitment to deepen CRTs to the entire Fannie Mae portfolio would potentially reduce the pricing gap at issuance.

I find that a form of signaling through delayed sales takes place. I verify that better quality loans tend to sell later, and worse ones earlier. When it comes to default, CRT loans exhibit this pattern. Indeed, Fannie Mae suffers losses when a loan defaults, which creates an incentive to pass the risk on to the investor. This is not the case when it comes to prepayment because CRT securities involve no transfer of prepayment risk. Investors recognize this, so they have no need to see a signal of prepayment quality. The results show that the relationship between timing and termination is compatible with incentives, rather than mechanically induced by the upward slope of default and prepayment hazard curves.

I find evidence of adverse selection in data disclosure, as the CRT loans that are among its publicly available data are of better quality than those that remain undisclosed. The findings support recent calls for the agencies to disclose their full portfolios in the public data, adding a flag to distinguish credit risk transfer loans.

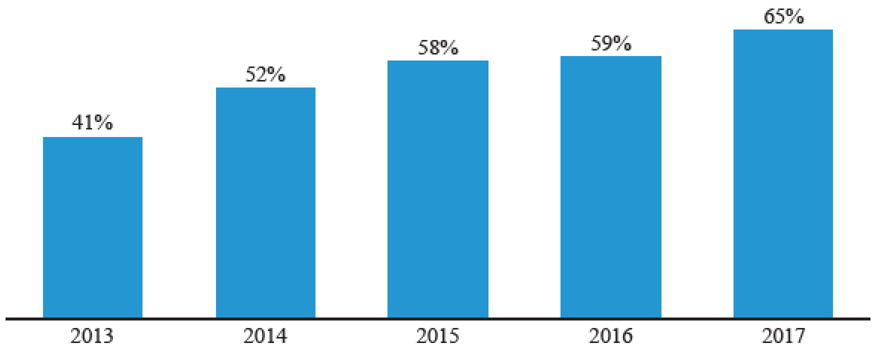


Figure 6.1: Single-family loans targeted for CRT, as a share of total acquisitions. Source: Goodman (2018).

Appendix

	Private label securities				Fannie Mae CRT			
	count	mean	sd	p50	count	mean	sd	p50
Spread (%)	1290	0.34	0.88	0.00	791	1.17	1.57	0.80
Tranche detachment point (%)	477	71.55	43.44	100.00	706	38.46	48.33	1.07
Year of issue	1290	2015.75	1.88	2015.00	791	2017.29	0.85	2017.00
Deal average LTV	621	76.92	14.29	71.94	579	81.51	6.47	82.54
Deal average FICO	654	727.01	52.11	756.65	579	748.79	3.65	747.17
Observations	1290				791			

Table 1: Summary of bond level data
This table summarizes the bond data (Fannie Mae CAS and private label loans) after applying the treatments described in Section 3. Loan characteristics at origination are averaged at the deal level summarized for all the loans in the initial sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Spread			
Fannie Mae CRT	0.833***	0.325***	0.246***	0.511***	0.556***	2.232***	2.652***
	(0.05)	(0.07)	(0.08)	(0.10)	(0.11)	(0.41)	(0.62)
Tranche detachment point		-0.009***	-0.010***	-0.010***	-0.009***	-0.000	-0.001
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average LTV			-0.002	-0.020***	-0.026***	-0.032	-0.145***
			(0.00)	(0.01)	(0.01)	(0.02)	(0.04)
Average FICO				-0.007***	-0.003**	-0.021***	-0.014***
				(0.00)	(0.00)	(0.00)	(0.00)
Vintage year	No	No	No	No	Yes	Yes	Yes
Initial rating	No	No	No	No	No	Yes	Yes
Interest rate index	No	No	No	No	No	No	Yes
Obs	2081	1183	807	805	805	243	208
R squ	0.10	0.17	0.21	0.23	0.28	0.36	0.36

Table 2: Pricing of CRT bonds - regression results
This table shows the output of a linear regression of bond spread at issuance (in percentage points) on a dummy for Fannie Mae CRT using bond origination data from Moody's ABSNet. The sample includes all Fannie Mae CRT and private label issues, excluding spreads based on WAC, keeping only tranches initially rated below A (or unrated). Tranche level controls include detachment point (i.e. the subordination cushion of the tranche that is immediately senior) and initial rating. Deal level controls include average FICO and LTV (weighted by loan size) and year of issue.

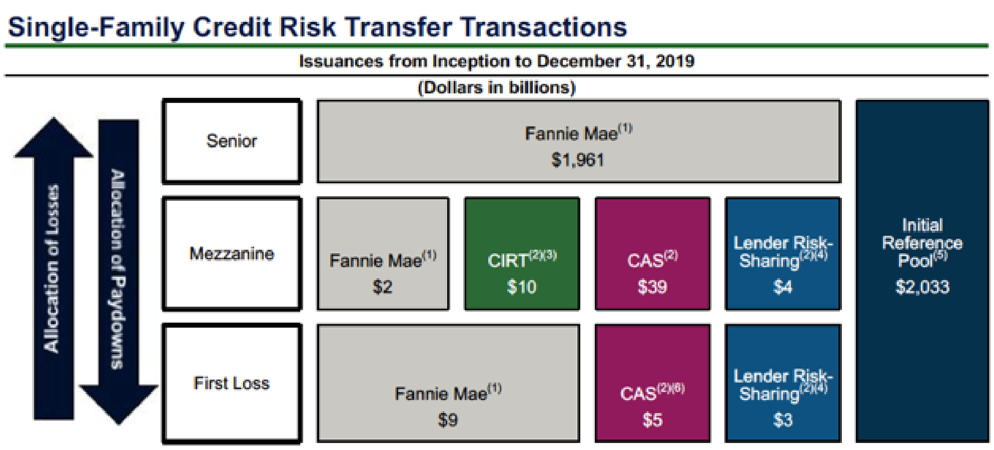


Figure 6.2: Source: Fannie Mae 10-K (2019)

	Private label loans				Fannie Mae CRT			
	count	mean	sd	p50	count	mean	sd	p50
Months to sale	661,247	97.8	47.5	106.0	4,876,185	11.9	3.5	12.0
Refinance indicator	733,319	0.5	0.5	1.0	4,876,185	0.4	0.5	0.0
Original balance (000)	738,056	244.2	251.9	158.0	4,876,185	238.2	118.1	219.0
Conforming by size	738,071	0.8	0.4	1.0	4,876,185	0.9	0.3	1.0
Original FICO	479,853	648.0	94.3	645.0	4,875,707	753.6	44.6	763.0
Original LTV	641,212	94.0	55.7	88.0	4,876,185	81.2	9.4	80.0
Prepayment penalty	738,071	0.0	0.2	0.0	4,876,185	0.0	0.0	0.0
Original loan term	724,097	358.2	85.6	360.0	4,876,185	359.7	3.9	360.0
Low documentation loan	738,071	0.0	0.2	0.0	4,876,185	0.0	0.0	0.0
Coupon gap	524,997	2.0	2.7	2.0	4,876,185	2.2	0.7	2.0
Origination year	738,071	2006.9	3.7	2006.0	4,876,185	2014.9	1.7	2015.0
Deal vintage year	738,071	2015.1	1.5	2015.0	4,876,185	2015.9	1.4	2016.0
Originated pre 2013	738,071	0.9	0.3	1.0	4,876,185	0.1	0.3	0.0
Debt to income ratio	0	.	.	.	4,876,182	34.0	8.8	35.2
Adjustable rate mortgage	738,071	0.3	0.5	0.0	4,876,185	0.0	0.0	0.0
Private mortgage insurance	738,071	0.5	0.5	0.0	4,876,185	0.8	0.4	1.0
PM insurance coverage	479,173	4.5	11.9	0.0	2,533,441	17.2	13.4	25.0
Credit event × 100	738,071	1.0	10.0	0.0	4,876,185	0.1	3.2	0.0
Default (90 days) × 100	738,071	13.6	34.2	0.0	4,876,185	0.9	9.5	0.0
Prepayment × 100	738,071	15.2	35.9	0.0	4,876,185	24.9	43.3	0.0

Table 3: Summary of raw Moody's ABSNet data - loan level
This table summarizes the ABSNet data (including Fannie Mae CRT and private label loans) before the cleaning steps described in Section3. Loan characteristics at origination are summarized for the full sample of loans.

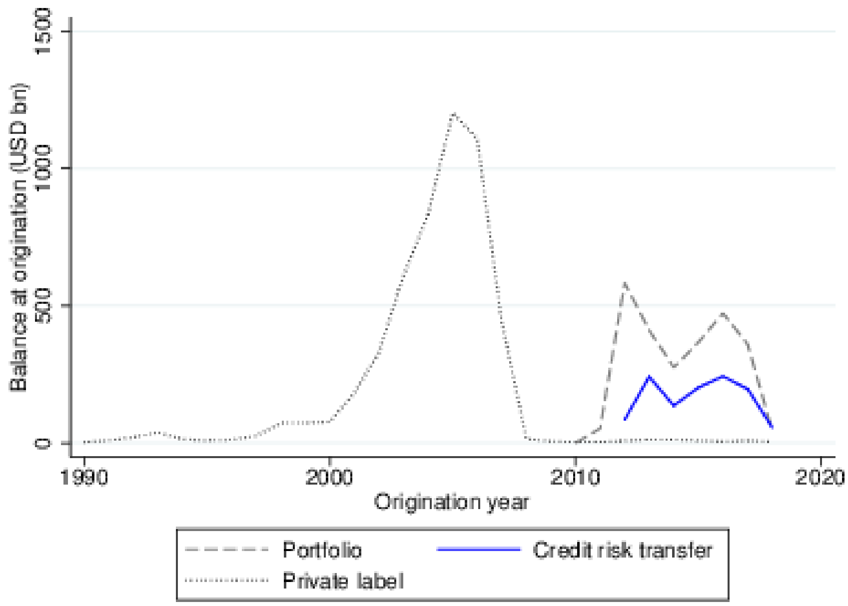
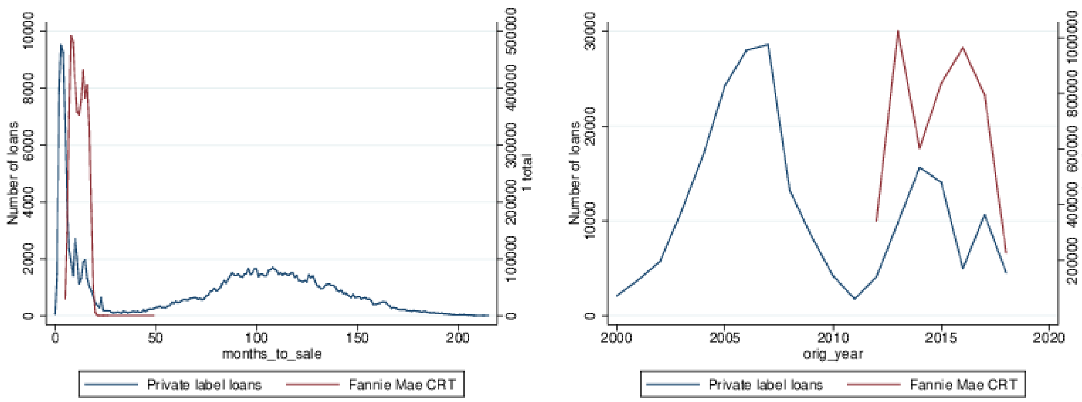


Figure 6.3: Aggregate origination volume by channel
This graph aggregates the loan origination amount from the Moody's ABSNet raw data as described in Table 3.

	Private label loans				Fannie Mae CRT			
	count	mean	sd	p50	count	mean	sd	p50
Months to sale	182,928	75.1	55.1	88.0	4,787,600	11.9	3.5	12.0
Refinance indicator	211,903	0.4	0.5	0.0	4,787,600	0.4	0.5	0.0
Original balance (000)	211,904	294.2	230.4	200.0	4,787,600	239.0	117.9	220.0
Conforming by size	211,904	0.7	0.4	1.0	4,787,600	0.9	0.3	1.0
Original FICO	96,253	731.1	58.5	746.0	4,787,128	753.6	44.6	763.0
Original LTV	136,408	77.5	17.1	80.0	4,787,600	81.2	9.5	80.0
Prepayment penalty	211,904	0.0	0.0	0.0	4,787,600	0.0	0.0	0.0
Loan term	211,904	360.0	0.2	360.0	4,787,600	360.0	0.0	360.0
Coupon gap	121,820	2.3	2.0	2.1	4,787,600	2.2	0.7	2.0
Origination year	211,904	2008.5	4.7	2007.0	4,787,600	2014.9	1.7	2015.0
Deal vintage year	211,904	2015.1	1.5	2015.0	4,787,600	2015.9	1.4	2016.0
Originated pre 2013	211,904	0.7	0.4	1.0	4,787,600	0.1	0.3	0.0
Adjustable rate mortgage	211,904	0.0	0.0	0.0	4,787,600	0.0	0.0	0.0
Private mortgage insurance	211,904	0.4	0.5	0.0	4,787,600	0.8	0.4	1.0
PM insurance coverage	141,940	3.7	11.3	0.0	2,489,275	17.3	13.4	25.0
Credit event $\times$ 100	211,904	1.9	13.8	0.0	4,787,600	0.1	3.2	0.0
Default (90 days) $\times$ 100	211,904	7.1	25.8	0.0	4,787,600	0.9	9.5	0.0
Prepayment $\times$ 100	211,904	13.5	34.2	0.0	4,787,600	25.1	43.4	0.0

Table 4: Summary of treated Moody's ABSNet data - loan level
This table summarizes the treated ABSNet data (Fannie Mae CRT and private label loans). Loan characteristics at origination are summarized for all the loans in the final sample used for estimation. Details about the treatment are explained in Section 3.



(a) Months to purchase

(b) Origination year

Figure 6.4: Distribution of time to sale and origination year across samples
The graphs provide counts of time to transaction (months) in the estimation sample. The left hand panel plots a count of months to sale for private label and Fannie Mae CRT loans in the sample shown in Table 4. The right hand panel plots the count of loans by origination year.

	(1)	(2)	(3)	(4)
		Coupon gap		
Credit risk transfer	0.236***	0.238***	0.199***	0.273***
	(0.07)	(0.07)	(0.07)	(0.07)
Original FICO		-0.003***	-0.003***	-0.003***
		(0.00)	(0.00)	(0.00)
Original LTV			0.002***	0.002***
			(0.00)	(0.00)
Refinance indicator			0.064***	0.063***
			(0.00)	(0.01)
Conforming by size			0.025***	0.021***
			(0.01)	(0.01)
Year-quarter	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Include legacy (pre-2013)	Yes	Yes	Yes	No
Obs	4909420	4835550	4827770	4468711
R squ	0.20	0.25	0.26	0.26

Table 5: Pricing of CRT loans relative to private label - regression results
This table shows the output of a linear regression of loan level coupon gap to 10-year Treasury (in percentage points) on a dummy for Fannie Mae CRT, using origination data from Moody's ABSNet. The sample includes all Fannie Mae CRT and private label mortgages following the treatments explained in Section 3.

	Fannie Mae data		Private label data	
Occurrences	Count	Cumulative frequency	Count	Cumulative frequency
1	12,818,043	99.55	26,345,258	97.27
2	54,460	99.97	550,214	99.3
3	3,018	99.99	80,064	99.6
4	812	100	31,404	99.71
5	155	100	14,835	99.77
6	90	100	9,522	99.8
7	14	100	6,083	99.83
8	24	100	4,872	99.84
10+	10	100	38,741	100
Total	12,876,626		27,080,993	

Table 6: Assessing the validity of the match between Moody's ABSNet and Fannie Mae data
This table provides a count of loan observations that have exactly the same values for the following set of characteristics: seller name, credit score (FICO), loan to value (LTV), loan amount, location of the property (at the MSA level) the date of origination (year-month). The table lists repetition counts for Fannie Mae data (left) and private label data (ABSNet, right) in terms of absolute counts and cumulative distribution. Note that both are supersets of the samples shown in Table 7 and Table 3, which only show observations after 2013.

	Fannie Mae portfolio				Fannie Mae CRT			
	count	mean	sd	p50	count	mean	sd	p50
Months to sale	0	.	.	.	1,369,815	12.2	3.6	12.0
Refinance indicator	11,448,228	0.6	0.5	1.0	1,369,815	0.4	0.5	0.0
Original balance (000)	11,448,228	224.4	120.6	200.0	1,369,815	237.5	113.4	220.0
Conforming by size	11,448,228	0.9	0.3	1.0	1,369,815	0.9	0.2	1.0
Original FICO	11,441,864	758.7	45.1	771.0	1,369,673	754.7	44.1	764.0
Original LTV	11,448,228	71.3	17.7	75.0	1,369,815	81.6	9.4	80.0
Original loan term	0	.	.	.	1,369,815	359.6	4.8	360.0
Low documentation loan	0	.	.	.	1,369,815	0.0	0.0	0.0
Coupon gap	11,448,228	1.9	0.7	1.9	1,369,815	2.2	0.7	2.0
Origination year	11,448,228	2014.3	1.9	2014.0	1,369,815	2014.9	1.7	2015.0
Debt to income ratio	11,446,005	32.7	9.4	34.0	1,369,815	33.9	8.7	35.0
Private mortgage insurance	11,448,228	0.2	0.4	0.0	1,369,815	0.4	0.5	0.0
PM insurance coverage	11,448,228	5.4	10.7	0.0	1,369,815	9.5	13.0	0.0
Months to GSE purchase	11,448,228	1.1	1.2	1.0	1,369,815	1.5	1.0	2.0
Credit event × 100	11,448,228	0.4	6.4	0.0	1,369,815	0.4	6.0	0.0
Default (90 days) × 100	11,448,228	0.9	9.3	0.0	1,369,815	0.8	8.7	0.0
Prepayment × 100	11,448,228	31.2	46.3	0.0	1,369,815	25.4	43.5	0.0

Table 7: Summary of raw Fannie Mae data - loan level
This table summarizes the raw Fannie Mae data (including the Fannie Mae CRT detected from matching with ABSNet data). Loan characteristics at origination are summarized for the full initial sample.

	Fannie Mae portfolio				Fannie Mae CRT			
	count	mean	sd	p50	count	mean	sd	p50
Months to sale	0	.	.	.	1,342,718	12.2	3.6	12.0
Refinance indicator	7,651,977	0.5	0.5	0.0	1,342,718	0.4	0.5	0.0
Original balance (000)	7,651,977	239.9	123.6	218.0	1,342,718	238.1	113.3	220.0
Conforming by size	7,651,977	0.9	0.3	1.0	1,342,718	0.9	0.2	1.0
Original FICO	7,647,475	756.2	45.0	767.0	1,342,578	754.7	44.0	765.0
Original LTV	7,651,977	74.9	16.5	80.0	1,342,718	81.6	9.5	80.0
Loan term	7,651,977	361.0	0.2	361.0	1,342,718	360.0	0.0	360.0
Coupon gap	7,651,977	2.2	0.6	2.0	1,342,718	2.2	0.7	2.0
Origination year	7,651,977	2014.4	1.9	2014.0	1,342,718	2014.9	1.7	2015.0
Debt to income ratio	7,650,170	33.7	9.2	35.0	1,342,718	34.0	8.7	35.1
Private mortgage insurance	7,651,977	0.3	0.4	0.0	1,342,718	0.4	0.5	0.0
PM insurance coverage	7,651,977	7.3	12.1	0.0	1,342,718	9.6	13.1	0.0
Months to GSE purchase	7,651,977	1.1	1.2	1.0	1,342,718	1.5	1.0	2.0
Credit event × 100	7,651,977	0.3	5.4	0.0	1,342,718	0.4	6.0	0.0
Default (90 days) × 100	7,651,977	0.7	8.3	0.0	1,342,718	0.8	8.7	0.0
Prepayment × 100	7,651,977	32.0	46.6	0.0	1,342,718	25.4	43.6	0.0

Table 8: Summary of treated Fannie Mae data - loan level
This table summarizes the treated Fannie Mae data (including the Fannie Mae CRT detected from matching with ABSNet data). Details about the treatment are explained in Section 3.

	(1)	(2)	(3)	(4)	(5)	(6)
			CRT loan × 100			
Original FICO	-0.003***					0.008***
	(0.00)					(0.00)
Original LTV		0.623***				0.650***
		(0.02)				(0.02)
Debt to income ratio			0.043***			-0.094***
			(0.00)			(0.01)
Coupon gap				0.198		-0.602***
				(0.17)		(0.15)
Hurricane county					2.544***	2.403***
					(0.57)	(0.37)
Year-quarter	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	No	No
Obs	12434603	12439577	12437767	12439577	11189689	11183363
R squ	0.07	0.10	0.07	0.07	0.06	0.10

Standard errors in parentheses. I cluster errors at state and origination year-quarter level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Comparison of loans sold and kept by Fannie Mae
This table provides the results of a linear probability regression on the Fannie Mae data. The dependent variable is an indicator for the loan being a Credit Risk Transfer relative to staying in portfolio. Independent variables are loan covariates observed at origination. I include origination year-quarter and state year-quarter fixed effects.

Shelf	Standard deviation	Interquartile range
ABMT	25.0	34
CAS	44.6	67
CHASE	30.4	47
CIM	44.6	58
CSMC	37.1	44
FSMT	34.4	48
JPMMT	31.3	43
SEMT	25.8	34
VOLT	31.5	39

Table 10: Disparity of loan quality across securitization shelves
This table summarizes the standard deviation and interquartile range of FICO score at origination for the most important shelves (by number of loans). CAS denotes Fannie Mae CRT, the rest of the acronyms standing for the most numerous private label securitization shelves.

	Private label			Fannie Mae CRT	
	(1)	(2)	(3)	(4)	(5)
Months to sale	-0.032***	-0.059***	0.008	-0.051***	-0.040***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Original FICO		0.013***	-0.012***		-0.020***
		(0.00)	(0.00)		(0.00)
Original LTV		-0.008	0.002		0.021***
		(0.01)	(0.00)		(0.00)
Refinance indicator		-0.404**	-0.030		0.143***
		(0.18)	(0.06)		(0.02)
Conforming by size		0.921***	0.379***		0.005
		(0.22)	(0.11)		(0.02)
Year-quarter	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes
Obs	182870	83163	54723	4787600	4787128
R squ	0.04	0.09	0.01	0.00	0.01

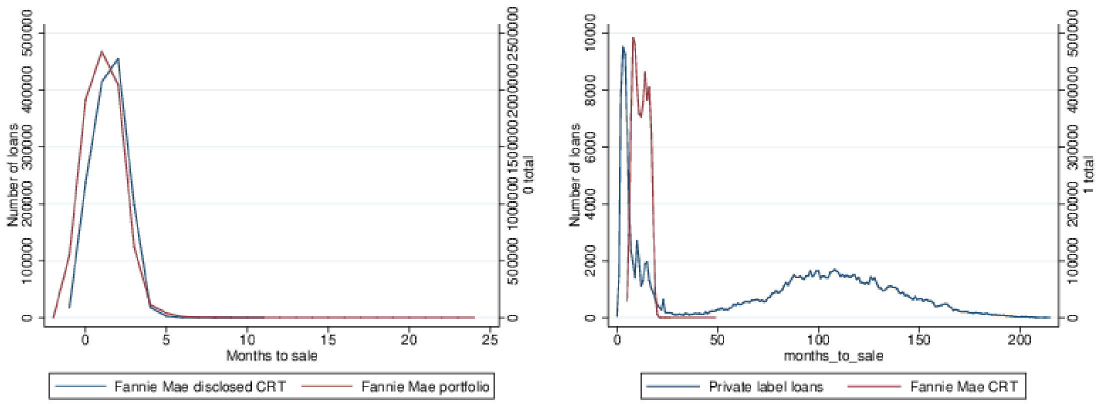
Standard errors in parentheses. I cluster errors at state and origination year-quarter level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Default probability and time to sale
This table summarizes the results of a linear regression of a default indicator (90 days past due) on time to private market sale of the loan, controlling for covariates at origination. The regression is estimated on the private label loan data, including loans that were initially on Fannie Mae's balance and those directly sold to private investors. The indicator variable for CRT denotes that the loan was part of a Fannie Mae CAS deal, as opposed to a pure private label loan.

	Private label			Fannie Mae CRT	
	(1)	(2)	(3)	(4)	(5)
Months to sale	-0.041***	-0.259***	-0.842***	-0.056	-0.015
	(0.01)	(0.03)	(0.06)	(0.05)	(0.05)
Original FICO		0.052***	-0.061***		-0.043***
		(0.01)	(0.01)		(0.00)
Original LTV		0.072***	0.066***		0.156***
		(0.01)	(0.02)		(0.01)
Refinance indicator		3.515***	0.130		2.589***
		(0.42)	(0.48)		(0.17)
Conforming by size		-3.211***	-0.051		-3.031***
		(0.65)	(0.81)		(0.42)
Year-quarter	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes
Obs	182870	83163	54723	4787600	4787128
R squ	0.16	0.13	0.17	0.14	0.15

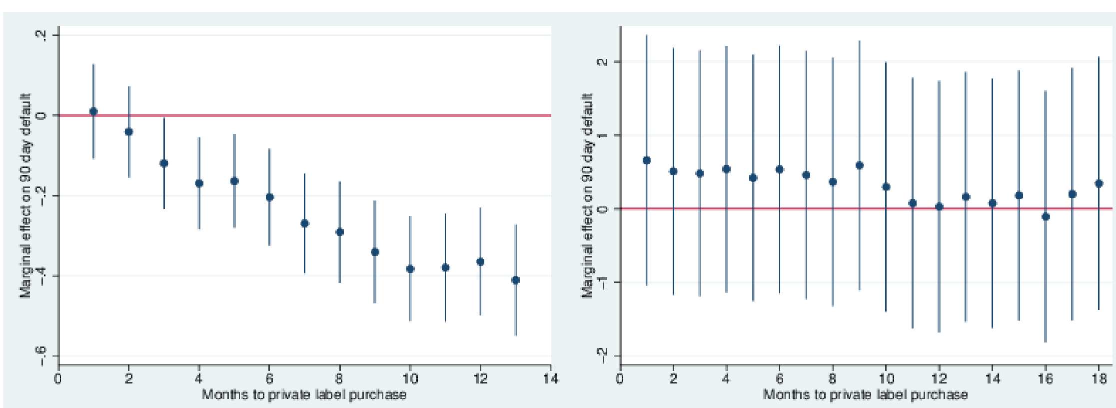
Standard errors in parentheses. I cluster errors at state and origination year-quarter level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Prepayment probability and time to sale
This table summarizes the results of a linear regression of a prepayment indicator on time to private market sale of the loan, controlling for covariates at origination. The regression is estimated on the private label loan data, including loans that were initially on Fannie Mae's balance and those directly sold to private investors. The indicator variable for CRT denotes that the loan was part of a Fannie Mae CAS deal, as opposed to a pure private label loan.

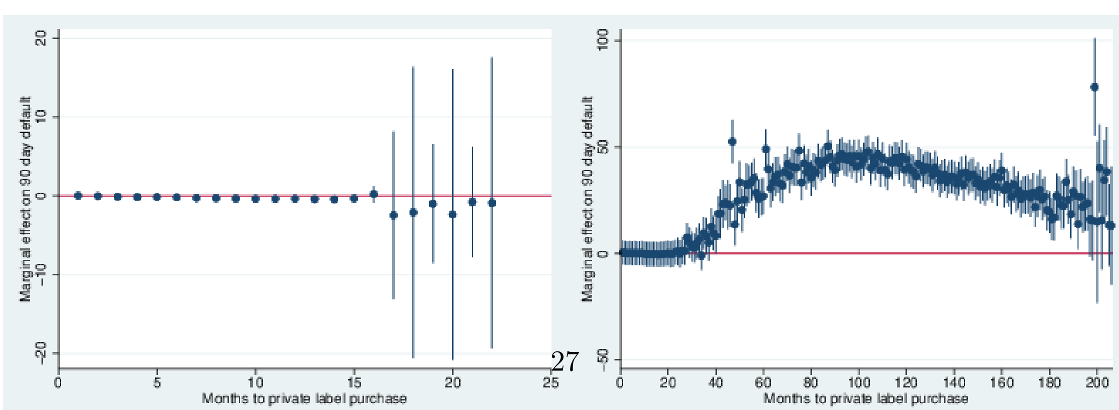


(a) Fannie Mae purchase (b) Private market sale

Figure 6.5: Distribution of seasoning across samples
The graphs provide density plots of time to transaction (months) in the estimation sample. The left hand panel plots the density to agency purchase for all Fannie Mae loans in the estimation sample. The right hand panel plots the density of private label sale time for Fannie Mae CRT and nonagency loans.



(a) CRT loans - first 18 months (b) Private label - first 18 months



(c) CRT loans - all months (d) Private label - all months

Figure 6.7: Marginal impact of month to sale on default probability
I regress a default indicator ($\times 100$) on a dummy variable indicating the month of sale, for both

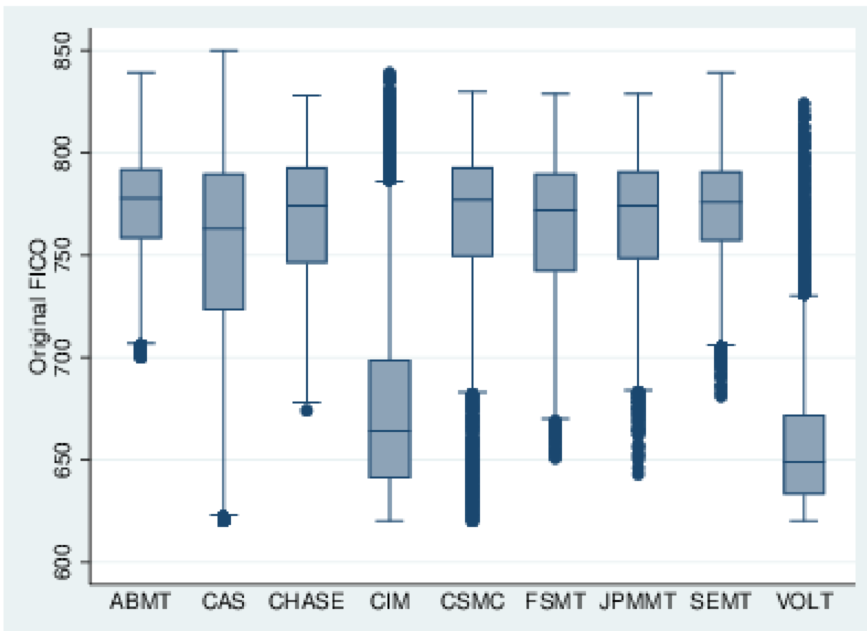
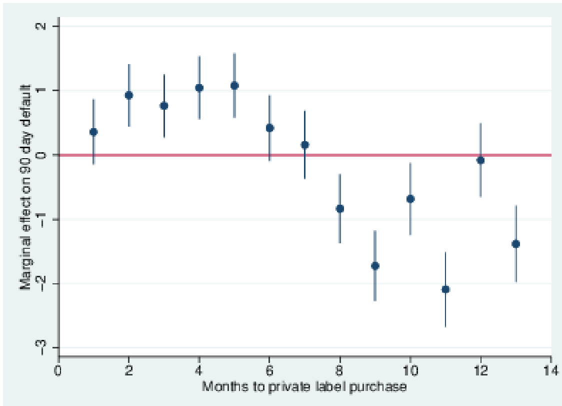
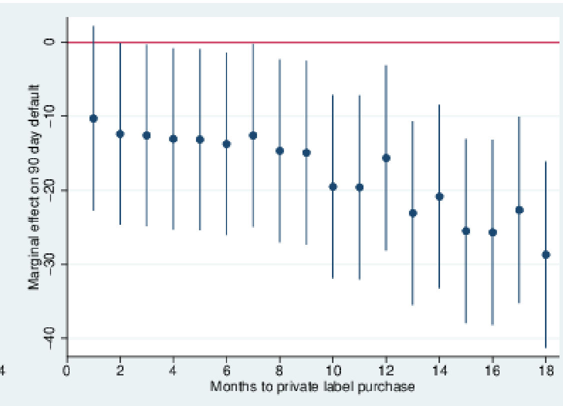


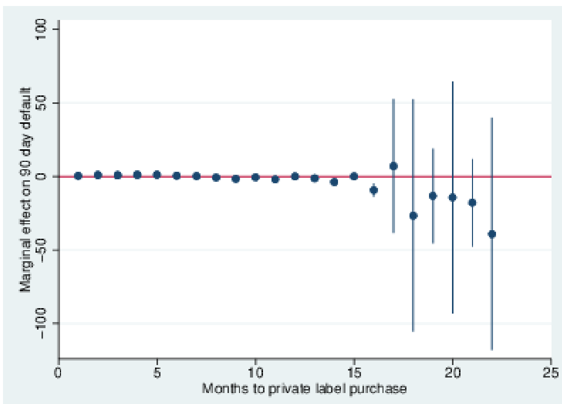
Figure 6.6: Distribution of FICO score across securitization shelves
The graphs provide box plots of original FICO score at origination for the most important shelves (by number of loans). CAS denotes Fannie Mae CRT, the rest of the acronyms standing for the most numerous private label securitization shelves.



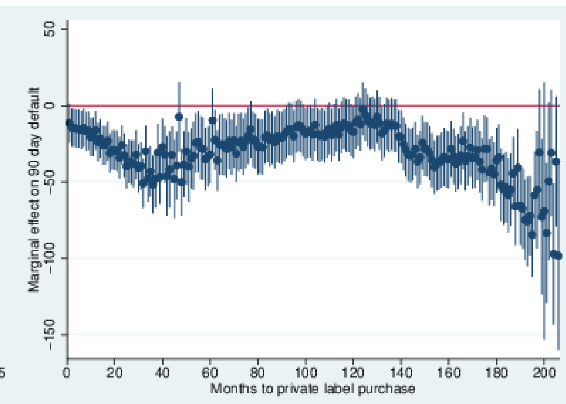
(a) CRT loans - first 18 months



(b) Private label - first 18 months

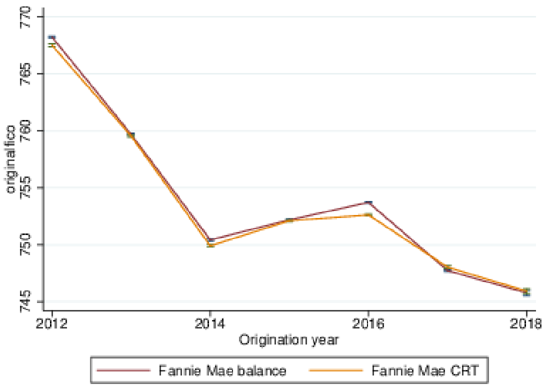


(c) CRT loans - all months

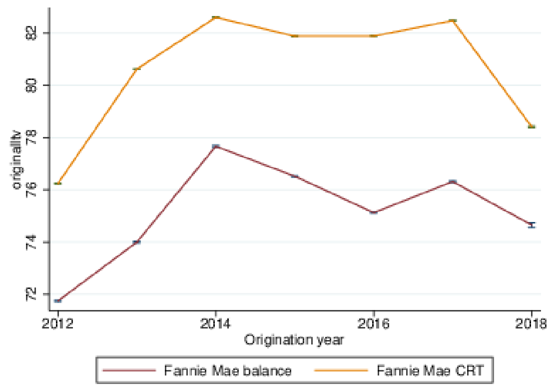


(d) Private label - all months

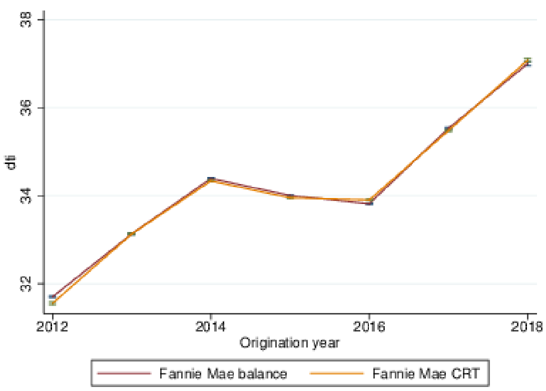
Figure 6.8: Marginal impact of month to sale on prepayment probability
I regress a prepayment indicator ($\times 100$) on a dummy variable indicating the month of sale, for both CRT and private label loans. The regressions include loan and borrower level controls, as well as year-quarter fixed effects. Vertical whiskers represent 95% confidence intervals.



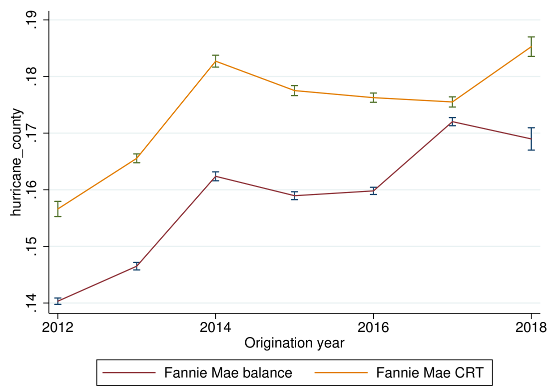
(a) FICO score



(b) LTV



(c) Debt to income ratio



(d) Hurricane county

Figure 6.9: Comparison of loan attributes within Fannie Mae data
For each of the above mentioned loan characteristics at origination, I plot the average value by loan origination year, splitting loans kept on balance and credit risk transfers. Vertical whiskers represent 95% confidence intervals.

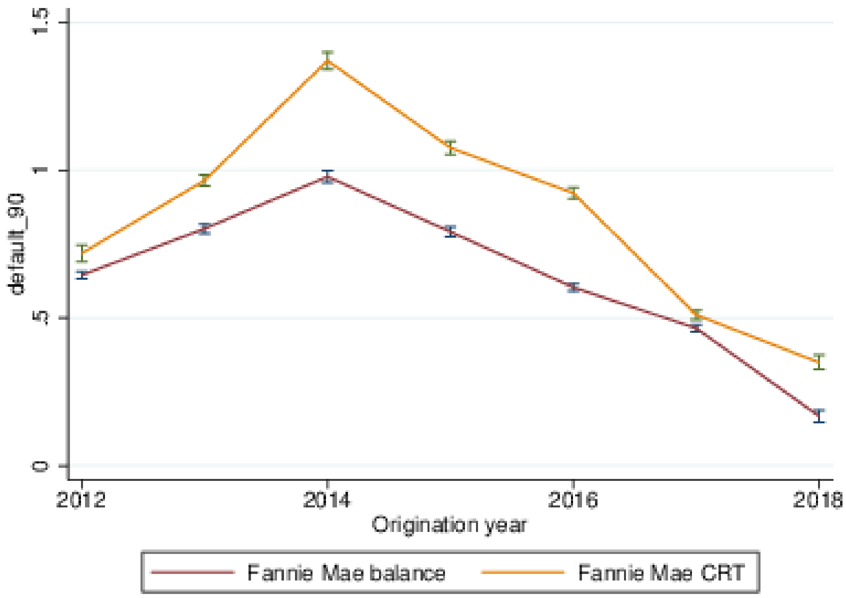


Figure 6.10: Comparison of loan performance within Fannie Mae data
I plot the 90 day delinquency rate by loan origination year, splitting loans kept on balance and credit risk transfers. Vertical whiskers represent 95% confidence intervals.

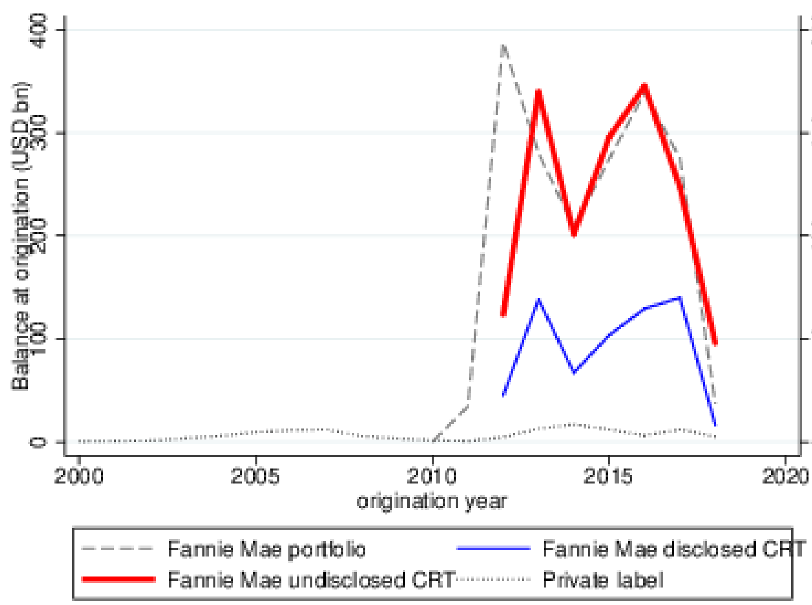
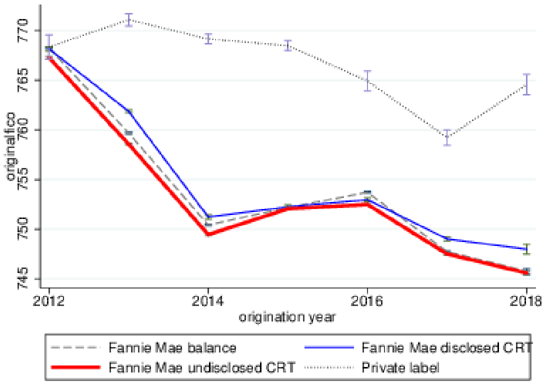
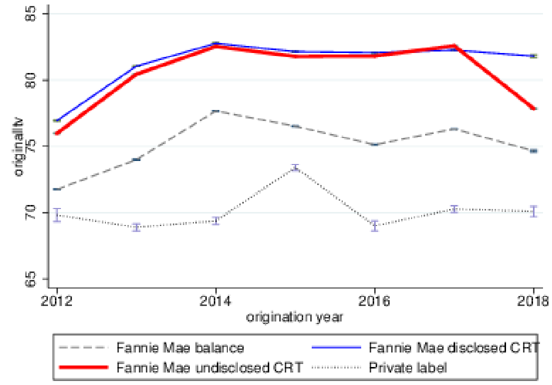


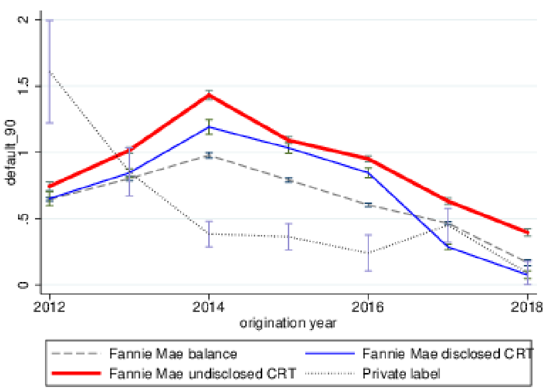
Figure 6.11: Aggregate origination volume by channel
This graph aggregates the loan origination amount from the Moody's ABSNet estimation sample as described in Table 4.



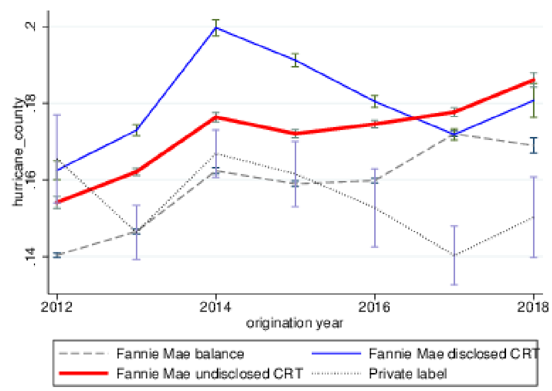
(a) FICO score



(b) LTV



(c) Default - 90 days (×100)



(d) Hurricane county

Figure 6.12: Comparison of disclosed and undisclosed CRT loans
I compare of origination and performance using the Fannie Mae data (where I find the unflagged but disclosed CRTs) augmented with the ABSNet (where I find the CRT flag and the set of loans undisclosed by Fannie Mae). For each of the above mentioned characteristics, I plot the average value by loan origination year, splitting Fannie Mae CRT loans into those that are disclosed and those that are not. Vertical whiskers represent 95% confidence intervals.

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