# The Impact of Skin in the Game on Bank Behavior in the Securitization Market

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## Abstract

Based on European RMBS deals with 21 million quarterly loan observations, we examine the effect of risk retention on bank behavior. Using pooled-OLS, propensity score matching and instrumental variable regressions, we analyze the reasons why no-retention-deals perform worse. Analyzing monitoring effort and the workout process, we find that the probability of rating updates or collateral revaluations is higher, and the rating quality is better. Retention-loans have a lower probability of becoming non-performing, a lower delinquency amount, a longer time until a loan becomes delinquent and a shorter time in arrears. Moreover, non-performing and defaulted retention-loans are more likely to recover. We observe that total losses are lower for deals with retention, which are driven by lower default rates, lower exposures at default, and higher recovery rates. Overall, our results suggest that retention reduces moral hazard and incentivizes banks to exert higher effort, which results in superior securitized asset performance.

*Keywords:* security design, asset-backed securities, retention, screening, monitoring

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# 1 Introduction

The design of asset-backed securities (ABS) has substantially contributed to the recent financial crisis; especially, the originate-to-distribute (OTD-) model had a huge impact on the development of the US subprime crisis. This business model enables banks to lend money to borrowers almost without bearing default risk because it is right away transferred to investors. Because of the very short exposure to the credit risk, banks lowered their screening and monitoring efforts and expanded their customer base to bad quality borrowers. Losses, which emerged from these incentive problems had to be borne by the investors of ABS. Against this background, retaining a fraction of an ABS transaction is expected to be helpful to harmonize the interests of banks and investors. We evaluate the originators having "skin in the game" by studying whether the bank behavior is more favorable in the presence of risk retention: Do banks treat securitized loans differently depending on retention, e.g. regarding screening, monitoring, or during the workout process?

Numerous research papers analyze the difference between securitized and balance sheet loans regarding loan characteristics and lenders actions, and recent research has shown that retention-deals perform worse (Begley/Purnanandam, 2017). However, the question *why* no-retention-deals perform worse, remains unanswered. Therefore, we investigate the effect of retention on monitoring activities for loans that are securitized in a deal with retention ("retention-loans") versus loans that are securitized in a deal without retention ("no-retention-loans"). Furthermore, we analyze the impact of retention on arrears prevention as well as the recovery of non-performing and defaulted loans. Additionally, while the literature has shown that delinquency rates are lower for retention-deals, we comprehensively analyze the impact of retention on the loss volume, and its decomposition into loss rate, exposure at default, as well as recovery rate. We evaluate this based on a data set of residential mortgage backed securities (RMBS) that is provided by the European DataWarehouse (EDW) of the ECB and consists of more than 21 million quarterly loan observations.

We are interested in the *within originator heterogeneity* regarding retention-loans and no-retention-loans. Therefore, we compare the behavior of originators towards retention-loans versus no-retention-loans in a given point of time. Using originator-time fixed effects and a set of controls, our setting allows for the comparison of loans which are securitized by the same originator and have similar loan characteristics at time *t* but differ only in the affiliation to a deal that is equipped with retention ("retention-deal") and a deal that is not equipped with retention ("no-retention-deal"). Additionally, we construct an instrumental variable to infer the causal effect of retention on our dependent variables.

To our knowledge, this paper is the first to investigate the impact of retention on the originators' behavior. We provide evidence for a reduction of moral hazard in the presence of risk retention by analyzing the originators behavior after loan securitization. We find that originators increase their effort to avoid losses: First, in the presence of retention, originators increase monitoring actions. This is indicated in significantly more frequent rating changes and collateral revaluations (both 3 times more likely for retention-loans) as well as a higher rating quality, which increases by 9% of the sample average. Second, in retention-deals, originators are more effective in preventing loans from becoming non-performing. Our results suggest that retention-loans have a 57% lower likelihood of becoming non-performing and the delinquency amount is 1,800 € smaller for retention-loans. Third, originators having skin in the game are more successful in the workout process of non-performing and defaulted loans. The time in arrears is reduced by more than 50 days and the probabilities of recovering from being non-performing or from default are both 36% higher for retention-loans. Regarding loan performance, our results suggest that retention helps to reduce losses of RMBS loans by about 120 € per loan and year, which is mainly driven by a 1.5 times lower default rate, a 17,000 € decreased exposure at default, and a 12 pp higher recovery rate. On the contrary, we find no evidence for adverse

selection since retention-loans hardly differ from no-retention-loans at the time of securitization, which supports the view that the more favorable outcome for retention-loans can be attributed to a higher effort in monitoring and during the workout process.

All in all, we provide evidence that agency problems in the securitization market can be mitigated by the security design. In fact, our analyses provide detailed information on the changes in the originators' behavior due to the originator having skin in the game. We offer a comprehensive image on the originators' actions in securitizations within retention-deals versus no-retention-deals.

We contribute to several streams of the literature, particularly regarding the security design, the financial crisis, and the impact of asymmetric information in banking. The impact of security design is a recent topic in the theoretical literature (Daley/Green, 2016; Sirignano et al., 2016; Williams, 2016; Hartman-Glaser, 2017; Sirignano/Giesecke, 2018; Hébert, 2018; Daley et al. 2019, forthcoming; Adelino et al., 2019). Theoretical literature also established that incentives are improved by retention, which assures the originator having "skin in the game". Combining pooling, tranching, and retention of the equity tranche has been shown to be a close approximation of the optimal security design (DeMarzo, 2005; Hartman-Glaser et al., 2012; Chemla/Hennessy 2014; Vanasco, 2017). Security design, especially the amount of retention, can be used to signal asset quality to uninformed investors. A governmental compulsory retention amount, though, impedes this signaling opportunity. Against this background, a prescribed flat-rate retention is socially suboptimal because of its information destruction effect (Leland/Pyle, 1977; Boot/Thakor, 1993; DeMarzo/Duffie, 1999; Hartman-Glaser, 2017; Guo/Wu, 2014; Vanasco, 2017). Retention, which is costly for the originator, seems to be a substitute to ratings as public information and reputation (Daley et al., forthcoming; Hartman-Glaser, 2017).

In contrast to the rich theoretical literature on retention, there are only few empirical findings. For the US pre-crisis RMBS market it has been shown that voluntary retention of a thicker equity tranche reduces the loan delinquency rate. Investors seem to benefit from the decline in

credit risk and lower the tranches' risk premiums: An above-median retention amount is associated with a 25 bp decrease in yield spreads and a reduction of abnormal defaults (Begley/Purnanandam, 2017). In the course of the Dodd-Frank-Act, mandatory retention seems to lead to lower credit risk, indicated by loans' risk premiums and default rates in the US (Agarwal et al., 2018). Furthermore, equity retention leads to a lower default probability of more senior tranches and lower spreads of tranches (Ashcraft et al., 2019; Flynn et al, 2019; Ciochetti/Larsson, 2017). Well-designed securitization contracts can improve screening incentives and reduce losses as well as tranches' defaults (Demiroglu/James, 2012; Malamud et al., 2013; Ghent et al., 2019). However, it remains unclear, how retention affects loan-level performance depending on the banks' behavior. We contribute to this strand of literature by disentangling the effect of retention on loan-level performance. We provide a comprehensive analysis on delinquencies, decompose the losses due to defaults and analyze the effort of recovering non-performing and defaulted loans using loan-level data.

A second related strand of literature deals with the contribution of ABS to the financial crisis. In the pre-crisis period, many originators used to securitize loans without retaining a material fraction of the deal. This practice is an integral part of the OTD-model as a main driver of the financial crisis. Because of the major lack of incentives, the OTD-model leads to a decreasing loan quality of securitized loans, especially if a bank is capital-constrained or has performed poorly in terms of negative stock returns. It has been shown that the increased securitization activity within the OTD-model, on the one hand, deteriorated the lenders' information gathering before loan origination and, on the other hand, led to the systematic securitization of worse loans (Berndt/Gupta, 2009; Keys et al., 2010; Titman/Tsyplakov, 2010; Purnanandam, 2011; Nadauld/Sherlund, 2013; Jiang et al., 2014). Moreover, loans, which are securitized after some time as balance sheet loans, are less risky than loans, which are securitized within the OTD-model. In line with that, recent research investigates the relationship between time to securitize and loan performance, pointing out that lemons seem to be sold first (An et al., 2011; Adelino

et al., 2019). We contribute to this literature by analyzing the relationship between retention and the time to securitization, showing that they both are substitutional commitments to monitoring and signals of loan quality.

A third stream of literature more broadly deals with asymmetric information in securitizations. These information asymmetries can be problematic, first, before loan origination between lender and borrowers, especially regarding the originators screening incentives (theoretically: Pennacchi, 1988; Gorton/Pennacchi, 1995; Holmstrom/Tirole, 1997; Petersen/Rajan 1994; empirically: Keys et al., 2010; Purnanandam, 2011; Griffin/Maturana, 2016). Second, information asymmetries can be problematic after loan origination and before securitization decision, indicating that the securitized pool is not a random sample of the originators' balance sheet loans and is used to remove undesired exposures from originators' balance sheets (Downing et al., 2009; An et al., 2011; Keys et al., 2010; Titman/Tsyplakov, 2010; Purnanadam, 2011; Agarwal et al., 2012; Ghent/Valkanov, 2016; Kara et al., 2019). Nevertheless, some studies find that there is no difference between securitized and balance sheet loans or that securitized loans even have better quality (Benmelech et al., 2012; Albertazzi et al., 2015). We contribute to this literature by demonstrating that retention does not affect loan quality at securitization significantly. Information asymmetries can be problematic, third, after loan securitization between originator and investor, if originators treat securitized loans differently regarding monitoring effort, modifications, renegotiations, as well as the probability of redefaults (Wang/Xia, 2014; Kara et al., 2019; Maturana, 2017 Piskorski et al., 2010; Agarwal et al., 2011; Zhang, 2013; Ghent/Valkanov, 2016; Kruger, 2018).We contribute to this literature by showing that the originators monitoring activities – measured by, rating changes, collateral revaluations, and rating quality – are improved in the presence of retention. Furthermore, we present evidence that retention mitigates delinquencies in terms of probability of becoming non-performing, delinquency amount, time in arrears, and probability of resolving non-performing loans and defaults.

The remainder of the paper is organized as follows. We describe our data set in Section 2 and present our empirical strategy in Section 3. We proceed with analyses of moral hazard (Section 4) and adverse selection (Section 5). The decomposition of losses in the presence of retention follows in Section 6. We establish the instrumental variable approach in Section 7. Section 8 concludes the findings.

## 2 Data

Subsequently, we describe the sample, we explain the measurement of relevant variables including the regulatory retention rules, and we present summary statistics of our data set.

### *2.1 Sample selection*

In the wake of the financial crisis, the European ABS market froze almost completely due to a lack of trust. To provide access to information about the quality of the underlying assets of eligible ABS and thereby regain trust in the ABS market, the ECB established the loan-level initiative. Market participants should be able to verify and to analyze the composition of a deal's pool before investing. In this respect, the EDW database was created aiming to increase transparency and restore "confidence in the [European] ABS market" (Trichet, 2011). Our data set consists of loan-level data from the EDW. We collect all quarterly submissions of European residential mortgage backed security (RMBS) deals, which are issued between 2009 and 2017, and track the submissions until the end of 2017. We exclude all loans, which have no unique identifier within a deal or have a negative time to maturity and all observations that have missings in at least one of our control variables. As we can track loans over time in EDW, our sample consists of more than 21.75 million different loan-quarter-observations of more than 2.3 million loans in 156 deals.

### *2.2 Variable measurement*

On January 1, 2011, the Capital Requirements Directive (CRD) introduced the minimum retention rules in Article 122a. Article 405 of the Capital Requirement Regulation (CRR) slightly re-defines minor aspects, and the current version of the retention rules is set in the European framework for securitizations. Since the introduction of the retention rules, the requirement of retention is fulfilled if "a material net economic interest in the securitization of not less than 5%" of the deal volume is retained. Investors located in the EU are only allowed to hold securitization positions if this retention requirement is fulfilled. However, if a deal is addressed to non-EU investors, it is possible to issue securitizations without retention after 2010. We provide further information and an overview of different retention types in the EU and the US in Appendix A.

We extract all retention information directly from the investor prospectuses. On deal level, we manually collect information about the deals' retention. To generate our binary key variable *Retention*, we search the prospectuses for retention information using the key words retain, retention, subordinated loan, 122a CRD, and 405 CRR. Since most originators only reveal that the deal fulfills the regulatory requirements, we assume that they choose the legal minimum of 5% (as Flynn et al. (2019) showed for the US). For deals that are issued before 2011, we only consider retention as fulfilled if the retention amount is at least 5% of the deals' nominal value to achieve consistency. If this threshold is not exceeded or there is no retention information available in the prospectuses, we assign no (qualified) retention. While in 2009 and 2010, there are only a few deals equipped with retention, the number of deals without retention drops dramatically throughout the introduction of the minimum retention rules in 2011. Notwithstanding, there are still some deals without retention after 2010. The distribution of retention across the sample period is presented in Table 1.

**Table 1 about here**

As dependent variables we use indicator variables for rating changes and valuation changes of the collateral, rating quality, Δrating quality, an indicator variable for non-performing loans, time to delinquency, time in arrears, delinquency amount, and indicator variables for delinquency recovery and default recovery. In addition, we use loss, an indicator variable for defaults, exposure at default and recovery rate as dependent variables. Appendix B provides an overview of the variable definitions. While most of these variables are direct dependent variables, we use the collateral value to infer the probability of valuation changes. The account status serves as a basis for defaults, non-performing loans and recovery for non-performing and defaulted loans. Table 2 presents descriptive statistics of the dependent variables. Some missing values are due to data quality, but most of them occur because some variables are only available in special cases, e. g. the exposure at default in case of default and the recovery rate, calculated as the cumulative recoveries two years after the default event. Except the internal credit rating, all required variables are mandatory for submissions to the EDW database.

**Table 2 about here**

For the internal credit rating as another dependent variable, we cannot provide descriptive statistics. The rating is considered as optional in the loan-level initiative and is unfortunately not standardized. As a result, each originator submits different rating classes. Examples for values of this variable are “CATTIVO”, “PAR A”, and “3200”. These various notations make it hard to compare ratings between deals, and very often difficult to determine a distinct rating scale within a deal. The most accurate variable to measure the rating systems’ evaluation of credit risk would be the probability of default (PD), which is, however, not provided. Nevertheless, for our analyses we do not need a continuous or ordinally scaled variable. Instead, when analyzing incentives, on the one hand, we use the frequency of rating changes as a proxy for

monitoring effort. On the other hand, we use the ability of each deal's rating system to predict future defaults as a proxy for the effort of reducing asymmetric information. Ultimately, we consider the internal credit rating as a nominally scaled variable and include the rating system as a set of indicator variables, which occur in a specific deal. For each loan-quarter observation only one indicator variable with the distinct rating of the loan in that period takes the value 1.

As control variables, we use a loan's *InterestRate* and *TimeToMaturity* as measures of credit risk. Additionally, in line with the finalization of the Basel III reforms, we use the *LoanToValue* as a key figure for real estate related exposures (BIS, 2017). *LoanBalance* (and the *Original-LoanBalance, respectively*) is an essential variable for the securitization decision and a proxy for risk concentration (Ghent/Valkanov, 2016). Table 3 provides summary statistics of the control variables. Loan balances with values of 0 occur for loans' last observations (redeemed loans), some first observations (e.g. if a loan is granted but not yet disbursed) or for defaulted loans (when the outstanding balance is flagged as defaulted).

Summing up the average deal characteristics, its size is 1.49 billion € and it consists of more than 15,000 loans. The average sample loan has an original volume of about 112,000 €, an interest rate of roughly 3.7%, and a remaining maturity of 21 years. The loan amount corresponds to about 74% of the collateral value.

**Table 3 about here**

## 3 Empirical strategy

Theory suggests that equipping deals with retention should harmonize the interests of originators and investors. If retention has the expected effect, we should find an improvement in the originators' behavior. For a given originator, we expect retention to increase monitoring effort, to decrease delinquencies and defaults, and to improve the workout process compared to his actions in a deal without retention. We conduct a within originator analysis indicating how a

given originator treats two loans that only differ in the fact of being assigned to a retention-deal or a no-retention-deal.

A major challenge is that the originators' actual actions and effort regarding these lender-borrower-relationships, and therefore the actual monitoring quality, are not observable. Hence, we have to use proxy variables for the originator's behavior. First, we investigate moral hazard in the presence of retention, controlling for loan characteristics. As proxy variables for the monitoring effort, we analyze the likelihood of rating changes, the likelihood of collateral revaluation, and the rating systems' ability to predict future defaults (rating quality). As proxy variables for the effort to prevent losses, we analyze the probability of becoming non-performing, the time a loan performs until it becomes non-performing. To analyze the incentives to modify and renegotiate loans, we examine the time in arrears, the delinquency amount, the likelihood of recovering non-performing loans, as well as the work out process, for which we analyze the likelihood of recovering defaulted loans. Second, we analyze if loan characteristics differ at loan securitization depending on retention, which would be an indication of adverse selection. Third, we provide a comprehensive analysis of losses, in which we disentangle the loss amount into default rate, exposure at default and recovery rate. Taken together, the different proxies of behavior transmit a convincing image of the effect of retention on incentives. Table 4 provides an overview about the subsequent analyses.

**Table 4 about here**

A potential concern is that the decision of assigning a loan to a retention- or a no-retention-deal is not exogenous, which could lead to systematical differences between retention-loans and no-retention-loans. Therefore, we have to deal with sources of endogeneity. We cannot fully eliminate these concerns, but, subsequently, we describe our empirical strategy to infer the effect of retention on the originators' behavior and support our findings with the established

theoretical argumentations. First, in our analyses regarding differences between retention- and no-retention-loans at the time of securitization, we do not find evidence for adverse selection. Second, we only consider deals of originators, which issued at least one retention-deal and one no-retention-deal. The purpose of this sample restriction is to achieve a comparison of each originator's loans, which are similar in as many characteristics as possible and only differ in the fact that they are assigned to a retention-deal or a no-retention-deal. Furthermore, this sample restriction reveals the *within* originator heterogeneity regarding retention-loans and no-retention-loans, indicating that the different behavior only depends on whether a loan is assigned to deal with or without retention. As support, several loan characteristics are used as control variables. To control for unobservable heterogeneity of originators, we include originator-time fixed effects.[2] As a result of this strategy, our analyzes reveal the within originator heterogeneity regarding retention-loans and no-retention-loans, indicating that the different behavior only depends on whether a loan is assigned to deal with or without retention. The resulting sample consists of 156 deals belonging to 27 different originators, which issue at least one deal with and one deal without retention within the sample period. We gain a sample of 40 no-retention-deals and 102 retention-deals. This sample consists of about 2.38 million different loans and 21.75 million quarterly observations.

We establish a basis model (equation 1), to which many of our analyses refer. Hence, for each relevant analysis, we introduce a dependent variable $Y_{i,t}$ below.

$$Y_{i,t} = \beta_0 + \beta_1 \cdot Retention_d + \delta \cdot Controls_{i,t} + \psi_{t\,x\,o} + \psi_y \tag{1}$$

The indicator variable $Retention_d$ is our variable of interest and takes the value 1 if a deal $d$ is a retention-deal, and 0 otherwise. Because loans with some characteristics might be treated differently to others, we add the vector $Controls_{i,t}$, which is a set of loan-level control variables

[2] Since originators only issue deals with assets from one country in our sample, originator-time fixed effects also control for country specific and country-time specific effects.

of loan *i* in time *t*, consisting of the *LoanBalance*, the *TimeToMaturity*, the *InterestRate*, and the *LoanToValue*. We provide all variable definitions in Appendix B. For example, one can argue that originators decide to monitor high-volume loans more frequently and more precisely because the monitoring costs per € loan are relatively low. Due to the time constant variable of interest – the indicator variable retention – we cannot employ a fixed effects transformation. Hence, we estimate all regression models as pooled OLS or pooled logistic regression. Originator-time fixed effects are indicated by $\psi_{t\,x\,o}$ and year-of-loan-origination fixed effects are indicated by $\psi_{y}$, since the time of loan origination correlates with a loan beeing a retention-loan and potentially with dependent variables like loan performance measures. Standard errors are heteroskedasticity robust and clustered on deal level for all regressions. Additionally to these regressions, we provide the results from an analogous propensity score matching for all loan level analyses in Appendix C. Finally, we implement an instrumental variables approach to infer the causal effect of retention. The construction of the instruments and the corresponding results are presented in Section 7. The instrument is constructed following Ashcraft et al. (2019) and indicates the originator's opportunity to securitize loans into no-retention-deals instead of retention deals to avoid losses from these loans. The originators may use this opportunity to assign loans with expected poor performance to a no-retention-deal and therefore to avoid losses from having skin in the game. The greater the percentage of no-retention-deals, the better the originator's expected monitoring of loans that are assigned to a retention-deal instead, and the better their performance. The results of the propensity score matching and of the instrumental variables approach both confirm our subsequent findings.

## 4 Skin in the game and moral hazard

Once the originator has securitized a loan into a no-retention-deal (and therefore has no skin in the game), he has no exposure to the loan's credit risk and therefore no incentive to avoid

possible losses (if reputational concerns are ignored). Therefore, the originator may refrain from costly checks of creditworthiness, renegotiations and modifications, as well as recovery and workout attempts. Subsequently, we investigate the originators' behavior regarding these aspects after a loan being securitized depending on the presence of retention.

### *4.1 Monitoring activities having skin in the game*

The proxy variables for monitoring activities are the likelihood of rating changes, the likelihood of collateral revaluations, and the rating quality. First, we investigate the likelihood of rating changes. If a loan's rating changes over time, this might be due to a new assessment of credit risk within the monitoring process; though, it cannot be ruled out that the rating change is due to a data failure or a redefinition of the rating system. While the latter reasons should not improve default prediction systematically, the rating quality should be enhanced if the rating change is the result of monitoring actions. Against this background, we test if updated ratings improve default prediction. Indeed, in 95% [89%] of the cases, rating changes improve default prediction significantly (at the 10% [1%] level). Another aspect of monitoring borrowers is the revaluation of the collateral; the result of this valuation can be a new collateral value. Thus, we investigate the probability of the collateral's valuation change. We perform a logistic regression of the indicator variables rating change and valuation change on retention as equation 1 indicates, including $Y_{i,t} = P(RatingChange_{i,t}=1|X_{i,t})$ and $Y_{i,t} = P(ValuationChange_{i,t}=1|X_{i,t})$ as dependent variables.

To conduct the first analysis, we generate an indicator variable *RatingChange*, which takes the value 1 if the rating of loan *i* in time *t* is different from the rating in time *t*-1, representing a rating change. Analogously to rating changes, we generate an indicator variable *ValuationChange*, which takes the value 1 if the collateral value has changed in the last period. We regress these indicator variables on *Retention* and the control variables. The results of the effect of

retention on the likelihood of rating changes (columns 1 and 2) and collateral revaluation (columns 3 and 4) are shown in Table 5.

**Table 5 about here**

The coefficients of the variable retention indicate that the likelihood of rating changes and collateral revaluation increase significantly if a deal is equipped with retention. This effect is economically very meaningful. The probability of both, rating changes and collateral revaluations, is around three times higher for retention-loans than for no-retention-loans. This finding suggests that the originators' incentives to avoid losses increase in the presence of retention, which is in line with the theoretical arguments.

As a second analysis regarding monitoring incentives, we investigate the rating quality. If the originator monitors borrowers, the result is a confirmation or revision of the existing credit rating. A good credit rating predicts future defaults accurately. Therefore, we conclude from a good credit rating system that monitoring effort is high. For this investigation, we estimate regression models on two levels. On the first level, we evaluate each deal's rating system using loan-level data. For this propose, we calculate the explanatory power of each rating system to predict future defaults. This first level regression is a logistic default prediction, where the probability of a loan defaulting within the next 12 months is estimated by the model in equation 2.

$$P(Default_{i,t+12} = 1 \mid X_{i,t}) = \beta_0 + \beta' \cdot CreditRating_{i,t} + \gamma' \cdot Controls_{i,t} + \psi_t \qquad (2)$$

$Default_{i,t+12}$ is an indicator variable, which takes the value 1 if the loan *i* defaults within the next four quarters and 0 otherwise. The vector *CreditRating* is a set of indicator variables for each rating class the deal's rating system consists of. Because there is no further information about the rating class scales, we consider credit rating as a nominally scaled variable. Since loans with some characteristics might be monitored more intensively, we add the vector *Con-*

*trols* on the first level, which consists of *LoanBalance*, *LoanToValue*, *TimeToMaturity* and *InterestRate.* As this regression is run for each deal separately, it is not possible to include originator-time fixed effects; instead, we add time fixed effects $\psi_t$ to control for the development of rating systems over time due to regulatory influence or macroeconomic effects.

We use the area under the ROC curve (AUC) for each deal *d* and time *t* as the measure of $RatingQuality_{d,t}$.[3] As a variation of this analysis, we analyze the improvement of a bank's rating system compared to a very simple rating system in order to achieve another measure of monitoring effort. We create the naïve rating system, which predicts future defaults on the set of loan-level characteristics from equation 1 but omits the interest rate as it is the result of the rating system. The area under the curve of the naïve rating system and, thus, the variable $RatingQuality_{d,t,naïve}$, are computed analogously. Afterwards, we generate the surplus of the originators' rating systems' ability to predict future defaults $\Delta RatingQuality$ by subtracting the coefficients of determination, as described in equation 3.

$$\Delta RatingQuality_{d,t} = RatingQuality_{d,t} - RatingQuality_{d,t,naïve} \quad (3)$$

Due to the fact that the credit rating is an optional variable in the ECB's data requirements, we restrict our sample for this analysis to deals, in which ratings are submitted in general; this reduces the sample by around 700,000 to 1.5 million different loans. The number of observations in Table 6 refers to the deal-quarter observations of the second level. In the first level, loan-level data are used. First level regression results cannot be provided because there is a set of regression tables for each deal, but we provide information on the explanatory power of the

[3] As a robustness check, we implement the pseudo-$R^2$ instead of the AUC as a measure of the rating quality (results available upon request). The average rating system explains 15% of the defaults in terms of pseudo-$R^2$. The estimated increase for retention-deals is about 5 percentage points. Thus, increase is economically meaningful since the rating quality is improved by about 33% of the sample average deal's capability of default prediction. Overall, these results are in line with the findings for the AUC.

average deal: The average rating system has an area under the curve of 78.7%, which is, on average, 5.5 percentage points better than the naïve rating system.

In the second level (equation 4), we relate the *RatingQuality* (or $\Delta RatingQuality$, respectively) to the existence of *Retention*$_d$.

$$\begin{aligned} Y_{d,t} &= \gamma_0 + \gamma_1 \cdot Retention_d + \psi_{t\,x\,o} + \varepsilon_d \\ with\ Y_{d,t} &= RatingQuality_{d,t}\ or\ Y_{d,t} = \Delta RatingQuality_{d,t} \end{aligned} \tag{4}$$

In this pooled OLS regression, originator-time fixed effects $\psi_{t\,x\,o}$ control for unobserved originator specific characteristics, and standard errors are clustered on deal level. The results of the second level are shown in Table 6. The highly significant coefficients of retention indicate that the deals' rating quality as well as the rating systems' surplus over our naïve rating system are significantly higher for retention-deals. This effect is economically meaningful since the rating quality is improved by about 6 percentage points. This is equivalent to 8% of the sample average deals' capability of default prediction.

**Table 6 about here**

Regarding this analysis, one could argue that the sample mainly consists of deals which are eligible to ECB to provide favorable refinancing for the originators. Relevant for the refinancing costs is the riskiness of the deal's tranches. To lower the riskiness, the originator can either improve the average loan quality in the pool or submit upward biased internal ratings to the ECB and rating agencies, holding the average loan quality constant. If this was the case, however, the default prediction of the ratings should deteriorate. Because we are not interested in the actual ratings, but rather in the ability to predict future defaults, such a concern regarding the sample selection does not apply.

Summing up, we find that retention is associated with an increase in the likelihood of rating changes, collateral revaluations, as well as with an improvement of rating quality, which are all

proxies for monitoring effort. These findings imply that originators treat loans differently if they have skin in the game.

### *4.2 Arrears prevention and recovering non-performing loans*

The next set of analyses refers to the originator's behavior if the borrower is already financially distressed. First, we look at the effort which is undertaken to prevent loans from becoming non-performing. Second, once a borrower is non-performing, we analyze the delinquency amount and the time in arrears. Third, we investigate the originators effort in recovering non-performing and defaulted loans.

Facing financially distressed borrowers, the originator can try to avoid that the borrowers become non-performing. For example, he can renegotiate the loan terms or agree to restructuring arrangements, e.g. reducing the redemption rate. This may put the borrower in the position to pay off the outstanding loan in good order. Necessary conditions for arrears prevention are the identification of impending financial distress and the willingness to prevent a loan from becoming non-performing. Analogously to the considerations in the sections before, the originator only has incentives to prevent losses and delinquency of loans if he has skin in the game. We expect the probability of becoming non-performing $P(NPL=1)$ to be decreased by retention. Sometimes however, restructuring arrangements might not be able to prevent delinquency but rather delay it. On average, given that a loan becomes non-performing, the time until then (*TimeToNPL*) increases if the originator makes effort to prevent loans from becoming non-performing. We therefore expect retention to generally increase the *TimeToNPL*.

To test this expectation, we run pooled OLS and pooled logistic regressions according to equation 1 with the dependent variables $Y_{i,t} = P(NPL)=1$ and $Y_{i,t} = TimetoNPL$. The indicator variable *NPL* is inferred from the account status and takes the value one if a loan status is in arrears and the time in arrears is greater than 30 days. The *TimeToNPL*, however, is computed

as the difference between the variables pool addition date and the date on which a loan status is changed to arrears. The results are presented in Table 7.

**Table 7 about here**

The coefficient of retention implies that the probability of becoming non-performing is 57% lower for retention-loans. The results in column (3) suggests that retention increases the time to NPL by 1.6 years, but the coefficient becomes insignificant if we include the interaction of originator and time fixed effects. In addition, the results show that riskier loans in terms of interest rates and LTV have higher probabilities of becoming non-performing and become non-performing faster.

The following analyses further investigate the originators' actions once a loan becomes non-performing. Taken as a basis for the following analyses, given a loan is non-performing, the sample average of time in arrears is 98 days, and the median is 60 days. The more effort the originator puts in identifying financial distressed and delinquent borrowers and the more willing he is to adjust loan terms, the faster delinquency can be resolved on average, holding all other factors constant. As skin in the game should increase these actions, we expect retention to decrease the time in arrears. In addition, an originator may not notice the borrower's financial distress until the first instalment of the loan is overdue, which implies that the borrower is delinquent. Consequently, given a loan is already non-performing, it is in the interest of an originator, who has skin in the game, to avoid a further increase of the delinquency amount. To achieve that, the originator may increase monitoring activities or renegotiate and modify loan terms. Thus, retention is expected to decrease the average delinquency amount of non-performing loans. The model is related to equation 1, with $Y_{i,t} = TimeInArrears_{i,t}$ or $Y_{i,t} = DelinquencyAmount_{i,t}$.

The time in arrears and the delinquency amount are both original variables of the EDW data set. The results are presented in Table 8. Retention effectively reduces the time in arrears by more than 50 days. This effect is highly statistically significant and economically meaningful. Retention also decreases the delinquency amount by about 1,800 €. This effect is not due to a different loan size as, first, retention-loans are on average larger and, second, loan size is included as a control variable. Regarding the control variables, we observe the plausible effect that loans that are riskier in terms of LTV tend to be in arrears for a longer period and have a higher delinquency amount. Moreover, less risky loans in terms of time to maturity tend to recover faster from delinquency and become delinquent with a smaller amount.

**Table 8 about here**

Another measurement of successful actions to avoid losses caused by non-performing loans is the recovery of non-performing loans. Following the loans' account statuses over time, we can track if a non-performing loan becomes performing again. For this case, we generate an indicator variable *NPLRecovery* which takes the value 1 if a non-performing loan's account status changes from non-performing in time $t$ to performing or redeemed in $t$+1. In case of no or unsuccessful actions, the indicator variable takes the value 0.

Similarly, during the workout process a defaulted loan can become performing again, and afterwards, credit terms are fulfilled and the loan is repaid orderly. Analogous to the recovery of non-performing loans, we introduce an indicator variable *DefaultRecovery*, which takes the value 1 if a defaulted loan's account status changes to performing or redeemed in the next period and 0 if it continues to be in default.

We estimate the recovery of non-performing loans $Y_{i,t} = P(NPLRecovery_{i,t}=1|X_{i,t})$ and the probability of default recovery $Y_{i,t} = P(DefaultRecovery_{i,t}=1|X_{i,t})$ with a pooled logistic regression model based on equation 1.

**Table 9 about here**

The results are presented in Table 9. Focusing on the recovery of non-performing loans, we find a highly significant and economically very meaningful effect of retention on modification and renegotiation incentives, indicating that the probability of recovery is 36% higher for retention-loans. The negative signs of the coefficients of the *InterestRate* and the *LoanToValue* suggest that riskier loans have a smaller probability of recovering. Additionally, if the outstanding amount of the loan is higher, recovery is a greater challenge. Completing the image, we find evidence that retention also helps to increase the probability of a recovery from default. The odds-ratio reports that the probability of recovering from default is 41% higher for retention-loans. These effects suggest that for retention-loans the originators try to maintain costumers' relationships and reconstitute their creditworthiness.

In conclusion, the results of this section present a comprehensive understanding on the practical relevance of retention for the prevention of losses from non-performing loans. At the bottom line, retention helps to reduce credit risk in many ways due to increased effort in the monitoring and workout process as suggested by the theoretical literature. Having shown that moral hazard seems to be mitigated by retention, we analyze if adverse selection is also a problem by investigating the loan characteristics at securitization.

## 5 Skin in the game and adverse selection

Retention-loans and no-retention-loans could already have different loan characteristics at the time of securitization, which is why we included several loan characteristics as control variables in the previous regressions. Subsequently, we return to the beginning of the loan securitization process and perform a comparison of loan characteristics between retention-loans and no-retention-loans, similar to Ghent and Valkanov (2016). Only the first observation of each

loan is included in this analysis, to infer possible differences at securitization. Table 10 shows the average loan characteristics for retention- versus no-retention-loans and provides the difference in means conducted by a *t*-test. For most variables, the univariate comparison suggests that no-retention-loans are slightly less risky than retention-loans, e.g., for the ratio of loan volume and collateral value (*LoanToValue*), the time to maturity or the loan balance, which is contrary to the expectations in case of adverse selection. Similarly, we do not find that retention increases the time to securitize, which could be expected based on the arguments that lemons are sold first.

**Table 10 about here**

Summing up, we do not find evidence for adverse selection at the time of securitization, which gives additional support of the finding that the higher monitoring effort after securitization for retention-loans is not based on different loan characteristics that exist already before securitization. In the last set of analyses, we investigate whether our findings are reflected in an improved loan performance for retention-loans.

## 6 Skin in the game and the decomposition of losses

In the previous analyses, we found a positive impact of retention on monitoring. Such improved incentives should ultimately lead to a better loan performance in terms of lower economic losses. Against this background, first, we investigate the effect of retention on loan losses. Afterwards, we decompose this effect, investigating the elements of loss. The empirical literature shows that non-securitized loans are of better quality and default less often than securitized loans (e. g. Ghent/Valkanov, 2016). Similarly, we find that retention is associated with a reduction in losses, which is in line with the existing literature (e. g. Begley/Purnanandam, 2017). Our main contribution to this strand of literature, however, is the decomposition of

losses. To paint this picture, we start our analyses with the investigation of the total loss amount from each loan. As the loss is the product of the default indicator, the exposure at default, and the loss given default, we disentangle the loss for each of these three factors by analyzing whether there are systematic differences for retention- vs. no-retention-loans. Equation 1 describes the regression models. In this set of analyses, our dependent variables are the Loss, an indicator variable *Default* if a loan will default in *t*+1, the *ExposureAtDefault*, and the *RecoveryRate* as the complement of the loss given default (=1–*RecoveryRate*).

$$\begin{aligned} &Y_{i,t} = Loss_{i,t} \;\; or \;\; Y_{i,t} = P\left(Default_{i,t+1} = 1 \mid X_{i,t}\right) \;\; or \\ &Y_{i,t} = ExposureAtDefault_{i,t} \;\; or \;\; Y_{i,t} = RecoveryRate_{i,t} \end{aligned} \tag{5}$$

Analyzing the default rates, we run pooled logit regressions; all other regressions are run as pooled OLS. For the analyses with the *ExposureAtDefault* as dependent variable, we control for loan size by including the original loan volume instead of loan balance (at default) because of collinearity. For exposure at default, the sample is restricted to defaulted loans.

The results are presented in Table 11. For deals with retention, the results suggest that the average loss per loan and year is about 120 € lower in the presence of retention. Decomposing the mechanism of retention to reduce losses, we find that retention helps to reduce the default rate. This effect is not only statistically significant, but also economically meaningful since the odds of defaulting are 1.5 times lower for retention-loans.[4] In line with expectations, the results further show that riskier loans in terms of LTV and interest rates are more likely to default. Furthermore, we find that retention has a substantial effect on the exposure at default, which is reduced by more than 17,000 €, controlling for *OriginalLoanBalance*. The slightly significant coefficient of the recovery rate suggests that retention has a large positive impact on the recovery rate, too (about 12 percentage points). We conclude from these findings that not only the

[4] A potential concern is that larger loans could have lower PDs, and, thus, the coefficient of retention in column (3) and (4) could be biased if retention was positively correlated with loan size. However, in Section 5, we showed that retention and loan size are negatively correlated.

avoidance of defaults is more effective in the presence of retention but also that once a loan is defaulted, having skin in the game provides incentives to the originator to carry out a cost-intensive workout process to avoid final losses. More precise, in the face of extremely likely losses, the originator tries to reduce them, e. g., by a more successful foreclosure or examination of future recovery payments.

**Table 11 about here**

## 7 Instrumental variable approach

To infer the causal effect of retention, we construct an instrument analogue to Ashcraft et al. (2019). While they provide evidence for the impact of skin in the game on CMBS deal and tranche level performance, we analyze the impact of skin in the game on the originators' behavior on loan level as well as the loan level performance as in the previous sections. The results of the pooled-OLS/logit regressions and the propensity score matching (see Appendix C) have shown that retention-loans are less exposed to moral hazard and perform better, and these findings hold after controlling for loan characteristics, originator and time fixed effects as well as originator-time fixed effects. The results illustrate the within originator heterogeneity in behavior regarding two loans that only differ in their assignment to a retention-deal or a no-retention-dal. Summing up, the results indicate that loans are monitored more appropriately if they are part of a retention-deal.

Although we do not find substantial differences between retention-loans and no-retention-loans at the time of securitization, one might argue that there might be endogeneity concerns; for example, the assignment decision might be driven by unobservable loan characteristics such as soft information that is obtained during the screening and monitoring process. If this information impacts the assignment decision and is correlated with our dependent variables for the originators' behavior and loan performance, the pooled-OLS/logit results might be biased.

Against this background, our performance results could be explained by two different mechanisms of retention. On the one hand, the assignment to a no-retention-deal after credit risk assessment in the screening and monitoring process might be more likely for loans that are expected to perform worse. In this case, the assignment to a no-retention-deal is an indication of future poor performance but not its cause. On the other hand, an originator of a no-retention-deal has weaker screening and monitoring incentives leading to poorer performance, which might drive our results. In this case, the relationship between retention and originators' behavior as well as loan level performance is causal.

To differentiate between the two explanations and to avoid potential selection bias, we construct an instrument for each deal *d* of originator *o* which is issued at time *t*. The instrumental variable is, analogous to Ashcraft et al. (2019), the moving average of the percentage of no-retention-deals by the same originator including all deals other than *d*, issued within in a window surrounding one year before and one year after the issuance of deal *d*. We adopt the variation of the "access" to no-retention-deals across time and originators which is measured by the instrument. Even though the percentage of new no-retention-deal issues diminishes over time because of the introduction of the minimum retention rules in 2011, we can still observe the behavior and the performance of earlier issuances. The effect, which is estimated by this instrument, is the impact of the originators opportunity to assign loans with expected poor performance to a no-retention-deal and therefore to avoid losses from having skin in the game. We expect that the greater the percentage of no-retention-deals, the better the originator's monitoring of loans that are assigned to a retention-deal instead, and the better their performance.

Regarding a potential violation of the exclusion restriction, it would be problematic if there were time-variant originator-specific characteristics, which are on the one hand correlated with the originator's share of no-retention-deals and on the other hand correlated with unobserved variables that correlate with our dependent variables. The introduction of the minimum retention rules is correlated with the probability that a deal is equipped with retention; however, it is

not correlated with our dependent variables via unobserved factors. We employ the same setting as for our pooled-OLS regressions, especially regarding sample restrictions, control variables and fixed effects. Since our instrument varies over time and originator, we can still implement originator fixed effects, time fixed effects and originator-time-fixed effects.[5] Table 12 shows the second stage results of IV regressions of our loan level related analyses.[6] We find that the signs of the coefficients from the IV setting remain the same as from our pooled-OLS regressions for all analyses, and in most cases the results remain statistically significant. Overall, the IV results confirm the effects of the pooled-OLS/logit regressions and of the propensity score matching, indicating that retention has a beneficial causal impact on the originators behavior.

**Table 12 about here**

## 8 Conclusion

The theoretical and empirical literature have shown that agency problems for securitized loans lead to a different treatment compared to balance sheet loans. We show that these agency problems along the credit process can be substantially mitigated by the security design, namely by risk retention. First, we show that retention increases monitoring effort, resulting in a higher probability of rating changes and collateral revaluations as well as a higher rating quality. Second, we show that originators prevent retention-loans from becoming non-performing. We not only provide evidence that the probability of becoming non-performing decreases in the presence of retention but also that the time until a loan becomes non-performing increases and the delinquency amount as well as the time in arrears decreases. Third, a recovery of non-performing and defaulted loans is significantly more likely if they are part of a retention-deal. The

[5] Note that the instrument is dependent on the year of deal issuance, whereas the fixed effects are dependent on the time of the observations, which avoids that fixed effects and our instrument are confounded.

[6] The results of the first stage regressions are available upon request.

preceding findings suggest that retention reduces moral hazard. Fourth, we find no evidence for an impact of retention on adverse selection since retention-loans and no-retention-loans hardly differ in terms of riskiness at the time of securitization. This indicates that the banks behavior *after* securitization is decisive for the difference in losses. Fifth, these improved incentives of the originator result in lower losses, which are a result of a lower default rate, exposure at default, and loss given default. This is beneficial to investors and helps to restore the trust in the securitization market since it harmonizes interests.

Summing up, we transfer theoretical arguments regarding the difference between balance sheet and securitized loans to retention- and no-retention-loans, and we provide empirical evidence that agency problems in the securitization market can be substantially mitigated by the security design. In fact, our analyses provide detailed information on the type and magnitude of changes in the originators' behavior. We offer a comprehensive image on the benefits of retention – providing insights on the way ABS should be designed to ensure trust and proper actions.

While we show that retention improves the effort in comparison to the absence of retention, due to data restrictions it remains unknown whether this level of effort is comparable to the effort which the originator would have taken if the loan was a balance sheet loan. Future research could, thus, analyze how a given originator, at a given point in time, treats three loans which are equal in all characteristics, however one is kept on the balance sheet, one is securitized in a no-retention-deal, and one is securitized in a retention-deal.

## Appendix A. Retention types

In the EU, there are five permitted retention types, which we briefly describe below. Equity retention is the retention of the first loss piece and, if essential, parts of the tranche above. Vertical slice retention is the retention of 5% of each issued tranche. Seller's share retention is the retention of 5% of the nominal value of each securitized exposure (only for revolving securitizations). For deals, in which the number of securitized exposures is at least 100, random selection is the retention of 5% randomly selected exposures, which otherwise would have been securitized. First loss retention is the retention of at least 5% of every securitized exposure.

For comparison, in the US the introduction of risk retention is announced by the Dodd Frank Act in 2010 and specified by the SEC in December 2014. Besides vertical slice retention and horizontal slice retention, a linear combination of them, L-shaped retention, is permitted. However, despite discussions, the EU decided against integrating L-shaped retention into the regulation since it is more complicated to implement (EBA, 2016). On top of the differences regarding the permitted retention types, there exist other distinctions between the European and US retention rules. While in the US the fair value of the deal is relevant for the calculation of the retention amount, the rules in the EU refer to the deals' nominal value. In case of the absence of market prizes, the fair value approach allows for valuation flexibilities. However, the disclosure requirements are stricter in the US, e.g. regarding the disclosure of risk parameters (Dodd Frank Act, 2010; SEC 2014; Krahnen/Wilde, 2017).

## Appendix B. Variable definitions

| Variable | Description | EDW Variable AR |
|---|---|---|
| *Default* | Indicator variable equal to one if a loan will default in $t$+1 | 166 |
| *DefaultRecovery* | Indicator variable equal to one if a loan is in default in $t$ and will become performing or will be redeemed in $t$+1 | 166 |
| *DelinquencyAmount* | Volume in arrears given a loan is delinquent (in €) | 169 |
| *ExposureAtDefault* | Outstanding balance in $t$ if a loan will default in $t$+1 (in €) | 67 |
| *InterestRate* | Current interest rate (in %) | 109 |
| *InternalRating* | Internal rating of a loan, measured by a set of indicator variables for each rating class of a deal's rating system | 17 |
| *LoanBalance* | Current loan balance (in thousand €) | 67 |
| *LoanToValue* | Current ratio of loan balance and collateral value (in %) | 141 |
| *Loss* | Default volume minus cumulative recoveries (in €) | 177, 181 |
| *NPL* | Indicator variable equal to one if a loan status is non-performing and the time in arrears is greater than 30 days. | 166 |
| *NPLRecovery* | Indicator variable equal to one if a loan is non-performing in $t$ and will become performing or will be redeemed in $t$+1 | 166 |
| *OriginalLoanVolume* | Loan volume at loan origination | 66 |
| *RecoveryRate* | Cumulative recoveries within 2 years after default divided by default volume | 177, 181 |
| *RatingChange* | Indicator variable equal to one if a loan's rating changes in the time between $t$ and $t$+1 | 17 |
| *RatingQuality* | Deal's rating system's capability to predict defaults within the next 12 months (pseudo $R^2$, measured in %) | 17 |
| *ΔRatingQuality* | Surplus of a deal's rating system's capability to predict defaults within the next 12 months over a naïve rating system's capability (measured in %-points) | 17 |
| *Retention* | Indicator variable equal to one for retention-loans (loans that are securitized in a deal with retention) and retention-deals | - |
| *TimeInArrears* | Number of days a loan is delinquent | 170 |
| *TimeToMaturity* | Number of months until date of loan maturity | 56 |
| *TimeToNPL* | Number of days between loan securitization and date of loan becoming non-performing | 166 |
| *TimeToSecuritize* | Number of months between loan origination and loan securitization | 55 |
| *ValuationChange* | Indicator variable equal to one if a loan's collateral value changes in the time between $t$ and $t$+1 | 136 |

Note: Variable names "AR" and definitions in the EDW database are provided within the ECB loan level initiative. See the RMBS data template here: https://www.ecb.europa.eu/paym/coll/loanlevel/transmission/html/index.en.html.

## Appendix C. Propensity score matching

Subsequently, we present the average treatment effects on the treated (ATT) resulting from a propensity score matching analogue to all previous loan level analyses. We match loans by their one nearest neighbor (with replacement), resulting from all our controls and indicators: interest rate, loan balance, LTV, time to maturity, loan origination year, originator and time. All results are in line with the OLS/logit estimators.

| Variable | Retention | No Retention | Difference | *t*-stat |
|---|---|---|---|---|
| Rating Change | 0.1200 | 0.0627 | 0.0574 | 29.21 |
| Valuation Change | 0.5164 | 0.4647 | 0.0517 | 37.31 |
| NPL | 0.2478 | 0.3970 | -0.1492 | -53.16 |
| Time to NPL | 902.96 | 487.09 | 415.87 | 20.72 |
| Time in Arrears | 103.64 | 137.06 | -33.42 | -13.33 |
| Delinquency Amount | 1,672 | 2,829 | -1,157 | -5.40 |
| Days in Arrears | 3.4954 | 8.3091 | 4.8137 | -31.54 |
| NPL Recovery | 0.3129 | 0.2427 | 0.0817 | 26.67 |
| Default Recovery | 0.0309 | 0.0167 | 0.0142 | 5.47 |
| Loss | 16.72 | 57.19 | -40.47 | -8.05 |
| Default | 0.0012 | 0.0012 | -0.000 | -0.09 |
| EAD | 122,752 | 134,829 | -12,077 | -1.18 |
| RR | 85.3 | 63.2 | 22.1 | 3.87 |

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# TABLES

**Table 1**
**Distribution of retention over time**

This table displays the number of no-retention and retention-deals issued per year (Panel A.1), the number of deal-level observations per year (Panel A.2), the number of loans per year of deal issuance (Panel B.1), and the number of observations of no-retention-loans and retention-loans in the data set (Panel B.2). Since the EDW database was introduced in 2012, regular submissions begin in 2012 and are tracked until 2017. However, the observations at securitization are available since the deals' issuance. No-retention-deal and no-retention-loan are assigned for deals without reported retention in the investor prospectus or with retention of less than 5%.

Panel A.1: Number of deals issued per year

| | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| No-Retention-Deals | 26 | 15 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 45 |
| Retention-Deals | 0 | 5 | 23 | 20 | 20 | 18 | 8 | 14 | 3 | 111 |
| Total | 26 | 16 | 24 | 21 | 10 | 19 | 8 | 14 | 3 | 156 |

Panel A.2: Observations of deals outstanding

| | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | Total |
|---|---|---|---|---|---|---|---|
| No-Retention-Deals | 15 | 43 | 43 | 39 | 28 | 24 | 192 |
| Retention-Deals | 22 | 68 | 83 | 90 | 100 | 90 | 453 |
| Total | 37 | 111 | 126 | 129 | 128 | 114 | 645 |

Panel B.1: Number of loans per year of deal issuance

| | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| No-Retention-Deals | 2163423 | 337,793 | 25,878 | 26,427 | 6,136 | 8,670 | 0 | 0 | 0 | 624,327 |
| Retention-Deals | 0 | 25,169 | 352,684 | 458,530 | 215,819 | 249,073 | 160,886 | 251,324 | 37,489 | 1,750,974 |
| Total | 216,423 | 362,962 | 378,562 | 454,957 | 224,995 | 257,743 | 160,886 | 251,324 | 37,489 | 2,375,301 |

Panel B.2: Observations of loans outstanding

| | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | Total |
|---|---|---|---|---|---|---|---|
| No-Retention-Loans | 151,781 | 1,687,639 | 1,725,583 | 1,343,288 | 915,621 | 317,263 | 6,141,175 |
| Retention-Loans | 219,292 | 3,306,839 | 3,517,008 | 3,860,282 | 3,484,213 | 1,495,945 | 15,613,577 |
| Total | 371,073 | 4,724,478 | 5,242,591 | 5,203,570 | 4,399,834 | 1,813,206 | 21,754,752 |

## TABLES

**Table 2**

**Descriptive statistics of dependent variables**

This table presents summary statistics of our dependent variables. N refers to the number of quarterly loan observations. For rating quality (and Δrating quality, respectively) only deal level observations are presented. Delinquency amount, loss and exposure at default are measured in Euro. Time in arrears and time to non-performing are measured in days. Time to securitize is measured in months. Rating change, valuation change, Non-performing loan (NPL), default, NPL recovery and default recovery are binary indicator variables. The recovery rate and rating quality is measured in percent, Δrating quality is measured in percentage points. We provide all variable definitions in Appendix B. To account for outliers, we winsorize the variables on the 99.5% level.

| | N | Mean | SD | Min | q50 | Max |
|---|---|---|---|---|---|---|
| Time to Securitize (month) | 12,878,232 | 35.5 | 19.1 | 0.9 | 33.5 | 117 |
| Rating Quality (%) | 417 | 78.60 | 10.05 | 50.70 | 79.19 | 98.90 |
| ΔRating Quality (%-p) | 417 | 5.47 | 8.34 | -14.23 | 2.78 | 29.66 |
| Rating Change (0/1) | 5,785,283 | 0.080 | 0.272 | 0 | 0 | 1 |
| Valuation Change (0/1) | 19,831,761 | 0.500 | 0.500 | 0 | 0 | 1 |
| NPL (0/1) | 21,754,752 | 0.000 | 0.2 | 0 | 0 | 1 |
| Time to NPL (days) | 35,937 | 439.9 | 540.3 | 1.0 | 1.0 | 1,188 |
| Time in Arrears (days) | 573,424 | 98.3 | 91.3 | 30 | 60 | 270 |
| Delinquency Amount (€) | 569,802 | 2,376 | 109,380 | 0 | 657.0 | 3,523,003 |
| NPL Recovery (0/1) | 468,274 | 0.324 | 0.468 | 0 | 0 | 1 |
| Default Recovery (0/1) | 111,606 | 0.034 | 0.181 | 0 | 0 | 1 |
| Loss (€) | 21,651,131 | 43.6 | 2920 | 0 | 0 | 613,363 |
| Default (0/1) | 21,735,015 | 0.001 | 0.1 | 0 | 0 | 1 |
| Exposure at Default (€) | 22,864 | 149,322 | 5,630,233 | 0 | 100,000 | 11,416,801 |
| Recovery Rate (%) | 9,168 | 88.2 | 31.5 | 0 | 100 | 100 |

**Table 3**

**Descriptive statistics of control variables**

This table provides information about all control variables. The sample consists of 2.38 million loans and 21 million observations. The interest rate and loan to value are measured in percent. Loan balance and original loan volume denote in Euro. Time to maturity is measured in months. We provide all variable definitions in Appendix B. To account for outliers, we winsorize the variables on the 99.5% level.

| | Mean | SD | Min | p25 | p50 | p75 | Max |
|---|---|---|---|---|---|---|---|
| Interest Rate (%) | 3.7 | 1.5 | 1.0 | 2.3 | 4.2 | 5.0 | 15 |
| Loan Balance (€) | 112,677 | 533,936 | 0 | 48,641 | 86,336 | 130,555 | 159,341,347 |
| Orig. Loan Vol. (€) | 133,200 | 655,635 | 0 | 63,506 | 100,000 | 149,588 | 178,645,500 |
| Loan to Value (%) | 74.1 | 33.4 | 0.0 | 49.4 | 75.8 | 99.0 | 143 |
| Time to Maturity (month) | 252.9 | 114.1 | 3.0 | 195.0 | 261.0 | 306.0 | 903 |
| N | 2,375,301 | | | | | | |
| NxT | 21,754,752 | | | | | | |

## TABLES

**Table 4**

**Overview of dependent variables and their purpose**

| Section | Purpose / Proxy for | Variable |
|---|---|---|
| 4.1 | *Moral Hazard* – Monitoring after Securitization | Rating Change<br>Valuation Change<br>Rating Quality<br>Δ Rating Quality |
| 4.2 | *Moral Hazard* – Restructuring and Workout of Non-Performing Loans | NPL<br>Time to NPL<br>Time in Arrears<br>Delinquency Amount<br>NPL Recovery<br>Default Recovery |
| 5 | *Adverse Selection* – at Loan Securitization | Time to Securitize<br>Interest Rate<br>Time to Maturity<br>Loan to Value<br>Loan Balance |
| 6 | Losses and Decomposition of Losses | Loss<br>Default<br>Exposure at Default<br>Recovery Rate |

**Table 5**

**Monitoring effort: Rating change and collateral revaluation**

This table contains the estimates of logistic regressions. Columns (1) and (2) refer to the analysis of the probability of rating changes and (3) and (4) refer to the probability of collateral revaluations (equation 1). We provide all variable definitions in Appendix B. Odd numbers refer to the regressions with originator and time fixed effects, even numbers to regressions with originator-time fixed effects. We include fixed effects for the year of loan origination in all regressions. Standard errors are clustered on deal level. *t* statistics are presented in parentheses. The signs denote as follows: $^{+}$ p < 0.10, $^{*}$ p < 0.05, $^{**}$ p < 0.01, $^{***}$ p < 0.001.

| | (1) Rating Change | (2) Rating Change | (3) Valuation Change | (4) Valuation Change |
|---|---|---|---|---|
| Retention | 1.293*** | 1.341*** | 0.988* | 1.122* |
| | (3.499) | (3.716) | (2.337) | (2.323) |
| Interest Rate | -0.030 | -0.092* | 0.117** | 0.157*** |
| | (-0.696) | (-2.547) | (2.961) | (4.250) |
| Log Loan Balance | 0.453+ | -0.054 | -0.191* | -0.294*** |
| | (1.728) | (-1.578) | (-2.561) | (-4.883) |
| Loan to Value | -0.004 | 0.004*** | 0.013*** | 0.014*** |
| | (-0.944) | (3.989) | (3.912) | (4.045) |
| Time to Maturity | -0.002* | -0.000 | 0.001* | 0.001** |
| | (-2.140) | (-0.842) | (2.372) | (3.260) |
| Constant | -9.159*** | 7.903*** | 3.989*** | 1.078 |
| | (-5.632) | (9.577) | (5.243) | (0.937) |
| Observations | 5,577,947 | 5,374,947 | 19,812,114 | 18,941,698 |
| Adj. Pseudo $R^2$ | 0.389 | 0.452 | 0.606 | 0.642 |
| *Fixed Effects* | | | | |
| Loan Origination Year | Yes | Yes | Yes | Yes |
| Originator | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Originator x Year | No | Yes | No | Yes |
| Clustered SE | Deal | Deal | Deal | Deal |

**Table 6**

**Rating quality**

The table contains the estimates of OLS regressions, in which the dependent variable represents the rating quality (equation 2). (1) and (2) refer to the quality of the actual rating system. (3) and (4) refer to the surplus of the rating system over a naïve rating system. Control variables are included on loan-level in the first level regressions. We provide all variable definitions in Appendix B. The sample is restricted to a subset of deals, which generally submit data regarding the variable internal credit rating and are issued between 2010-2016 to provide at least one full year of default predictions. Odd numbers refer to the regressions with originator and time fixed effects, even numbers to regressions with originator-time fixed effects. Standard errors are clustered on deal level. *t* statistics are presented in parentheses. The signs denote as follows: $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

| | (1) Rating Quality | (2) Rating Quality | (3) ΔRating Quality | (4) ΔRating Quality |
|---|---|---|---|---|
| Retention | 0.070*** | 0.063*** | 0.070*** | 0.051*** |
| | (11.391) | (12.219) | (8.613) | (11.908) |
| Constant | 0.738*** | 0.633*** | 0.064*** | -0.041+ |
| | (120.535) | (27.988) | (7.834) | (-1.771) |
| Observations | 417 | 417 | 417 | 417 |
| Adj. $R^2$ | 0.597 | 0.550 | 0.612 | 0.581 |
| 1st Level Controls | Yes | Yes | Yes | Yes |
| *Fixed Effects* | | | | |
| Loan Origination Year | No | No | No | No |
| Originator FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Originator x Time FE | No | Yes | No | Yes |
| Clustered SE | Deal | Deal | Deal | Deal |

**Table 7**

**Preventing non-performing loans**

Columns (1) and (2) refer to the analysis of the probability of becoming non-performing and (3) and (4) refer to the time to become non-performing (equation 1). We provide all variable definitions in Appendix B. Odd numbers refer to the regressions with originator and time fixed effects, even numbers to regressions with originator-time fixed effects. We include fixed effects for the year of loan origination in all regressions. Standard errors are clustered on deal level. *t* statistics are presented in parentheses. The signs denote as follows: $^{+}$ p < 0.10, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | NPL | NPL | Time to NPL | Time to NPL |
| Retention | -0.554$^{*}$ | -0.554$^{*}$ | 596.022$^{***}$ | -3.652 |
| | (-2.349) | (-2.284) | (9.199) | (-0.261) |
| Interest Rate | 0.104$^{***}$ | 0.097$^{***}$ | -12.337$^{**}$ | -10.960$^{*}$ |
| | (4.046) | (3.892) | (-3.313) | (-2.507) |
| Log Loan Balance | 0.136$^{***}$ | 0.136$^{**}$ | 24.723$^{*}$ | 26.631$^{*}$ |
| | (3.399) | (3.224) | (2.221) | (2.342) |
| Loan to Value | 0.016$^{***}$ | 0.017$^{***}$ | -4.180$^{**}$ | -4.129$^{**}$ |
| | (4.672) | (4.490) | (-3.570) | (-3.297) |
| Time to Maturity | -0.001$^{*}$ | -0.001$^{*}$ | -0.688 | -0.628 |
| | (-2.134) | (-2.480) | (-1.219) | (-1.022) |
| Constant | -8.227$^{***}$ | -8.796$^{***}$ | -1352.345$^{**}$ | -1138.247$^{***}$ |
| | (-9.909) | (-11.626) | (-3.205) | (-7.146) |
| Observations | 21,726,283 | 21,726,283 | 35,937 | 35,937 |
| Adj. $R^2$/Adj. Pseudo $R^2$ | 0.071 | 0.077 | 0.697 | 0.726 |
| *Fixed Effects* | | | | |
| Loan Origination Year | Yes | Yes | Yes | Yes |
| Originator | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Originator x Year | No | Yes | No | Yes |
| Clustered SE | Deal | Deal | Deal | Deal |

**Table 8**

**Treating non-performing loans**

This table contains the estimates of pooled OLS regressions. Columns (1) and (2) refer to the analysis of the time in arrears given a loan is non-performing and (3) and (4) refer to the delinquency amount given a loan is non-performing (equation 1). We provide all variable definitions in Appendix B. Odd numbers refer to the regressions with originator and time fixed effects, even numbers to regressions with originator-time fixed effects. We include fixed effects for the year of loan origination in all regressions. Standard errors are clustered on deal level. *t* statistics are presented in parentheses. The signs denote as follows: $^{+}$ p < 0.10, $^{*}$ p < 0.05, $^{**}$ p < 0.01, $^{***}$ p < 0.001.

| | (1) Time in Arrears | (2) Time in Arrears | (3) Delinquency Amount | (4) Delinquency Amount |
|---|---|---|---|---|
| Retention | -56.223*** | -54.359*** | -1,858.528* | -1,828.973* |
| | (-4.094) | (-3.800) | (-2.459) | (-2.312) |
| Interest Rate | -0.622 | -0.297 | -123.129 | -112.633 |
| | (-0.280) | (-0.140) | (-1.047) | (-1.041) |
| Log Loan Balance | 5.855 | 5.937 | | |
| | (1.396) | (1.388) | | |
| Loan Balance | | | 6.920*** | 9.143** |
| | | | (8.611) | (2.724) |
| Loan to Value | 2.027*** | 1.928*** | 55.182* | 49.847* |
| | (5.179) | (5.379) | (2.035) | (2.031) |
| Time to Maturity | -0.181* | -0.181* | -11.978* | -11.770* |
| | (-2.475) | (-2.580) | (-2.205) | (-2.097) |
| Constant | -52.454 | -32.887 | 4096.710** | 3704.151* |
| | (-1.056) | (-0.860) | (2.965) | (2.078) |
| Observations | 569,520 | 569,520 | 464,774 | 464,774 |
| Adj. $R^2$ | 0.154 | 0.172 | 0.129 | 0.165 |
| *Fixed Effects* | | | | |
| Loan Origination Year | Yes | Yes | Yes | Yes |
| Originator | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Originator x Year | No | Yes | No | Yes |
| Clustered SE | Deal | Deal | Deal | Deal |

**Table 9**

**Restructuring and modification**

This table contains the estimates of logistic regressions analyzing the recovery probabilities. Columns (1) and (2) refer to the recovery of non-performing loans, and (3) and (4) refer to the recovery of defaulted loans (equation 1). We provide all variable definitions in Appendix B. Odd numbers refer to the regressions with originator and time fixed effects, even numbers to regressions with originator-time fixed effects. We include fixed effects for the year of loan origination in all regressions. Standard errors are clustered on deal level. *t* statistics are presented in parentheses. The signs denote as follows: $^{+}$ p < 0.10, $^{*}$ p < 0.05, $^{**}$ p < 0.01, $^{***}$ p < 0.001.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | NPL Recovery | NPL Recovery | Default Recovery | Default Recovery |
| Retention | 0.312*** | 0.334*** | 0.389* | 0.345+ |
| | (5.126) | (5.477) | (2.433) | (1.883) |
| Interest Rate | -0.061*** | -0.059*** | 0.065 | 0.052 |
| | (-5.850) | (-5.281) | (0.591) | (0.455) |
| Log Loan Balance | -0.039* | -0.041* | -0.061 | -0.084* |
| | (-2.245) | (-2.438) | (-1.273) | (-2.068) |
| Loan to Value | -0.005*** | -0.005*** | -0.009*** | -0.007** |
| | (-4.293) | (-4.610) | (-3.718) | (-3.232) |
| Time to Maturity | 0.000 | 0.000 | 0.002* | 0.002* |
| | (0.092) | (0.673) | (2.105) | (2.189) |
| Constant | -1.553 | -0.957 | -2.062 | -1.372 |
| | (-1.243) | (-0.743) | (-1.372) | (-1.370) |
| Observations | 467,901 | 467,407 | 62,652 | 61,641 |
| Adj. Pseudo $R^2$ | 0.039 | 0.046 | 0.093 | 0.102 |
| *Fixed Effects* | | | | |
| Loan Origination Year | Yes | Yes | Yes | Yes |
| Originator | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Originator x Year | No | Yes | No | Yes |
| Clustered SE | Deal | Deal | Deal | Deal |

**Table 10**

**Loan characteristics - differences in means**

In this table, we provide the average loan characteristics at securitization. We group no-retention-loans and retention-loans and provide the difference in means as well as the *t*-test of this difference. We provide all variable definitions in Appendix B.

| | No Retention | Retention | Difference | p-value | *t*-stat |
|---|---|---|---|---|---|
| Time to Securitize | 43.15 | 36.05 | 7.10 | 0.00 | 153.21 |
| Interest Rate | 3.86 | 3.76 | 0.10 | 0.00 | 44.15 |
| Time to Maturity | 253.46 | 283.80 | -30.34 | 0.00 | -173.33 |
| Loan to Value | 82.73 | 83.18 | -0.45 | 0.00 | -3.89 |
| Loan Balance | 219,687.88 | 226,378.84 | -6,690.95 | 0.01 | -2.70 |

**Table 11**

**Decomposition of losses**

This table contains the estimates of pooled OLS and logit regressions (equation 1). Columns (1) and (2) refer to the analysis of the loss amount and (3) and (4) refer to the default status in $t$+1 (pooled logit), (5) and (6) refer to the exposure at default (EAD) and (7) and (8) refer to the recovery rate (RR). For EAD, the sample is restricted to defaulted loans. For RR, the sample is restricted to defaults with completed workout process. We provide all variable definitions in Appendix B. All regressions are run with originator and time fixed effects (odd numbers) or originator-time fixed effects (even numbers). We include fixed effects for the year of loan origination in all regressions. Standard errors are clustered on deal level. $t$ statistics are presented in parentheses. The signs denote as follows: $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Loss | Loss | Default | Default | EAD | EAD | RR | RR |
| Retention | -31.359$^{*}$ | -29.321$^{*}$ | -0.426$^{*}$ | -0.401$^{*}$ | -13,648.860 | -17,050.685$^{*}$ | 12.812$^{+}$ | 12.138$^{+}$ |
| | (-2.204) | (-2.107) | (-2.230) | (-2.067) | (-1.064) | (-2.282) | (1.806) | (1.722) |
| Interest Rate | 2.337$^{+}$ | 3.016$^{+}$ | 0.158$^{***}$ | 0.139$^{***}$ | 481.982 | -5049.841$^{***}$ | 0.166 | 0.076 |
| | (1.681) | (1.912) | (5.536) | (4.819) | (0.296) | (-6.914) | (0.613) | (0.279) |
| Log Loan Balance | 25.904$^{**}$ | 26.654$^{**}$ | 0.096$^{+}$ | 0.089 | | | -1.065 | -1.232 |
| | (3.139) | (3.131) | (1.750) | (1.544) | | | (-1.627) | (-1.553) |
| Loan to Value | 0.210$^{*}$ | 0.192$^{*}$ | 0.025$^{***}$ | 0.026$^{***}$ | 290.992$^{**}$ | 405.341$^{***}$ | 0.001 | -0.003 |
| | (2.563) | (2.423) | (7.505) | (6.530) | (3.318) | (4.087) | (0.092) | (-0.260) |
| Time to Maturity | 0.006 | 0.006 | -0.001 | -0.001$^{+}$ | 116.946$^{***}$ | 132.353$^{***}$ | 0.004 | 0.003 |
| | (0.413) | (0.408) | (-1.303) | (-1.792) | (3.818) | (5.279) | (0.739) | (0.567) |
| Original Loan Volume | | | | | 0.493$^{***}$ | 0.150$^{***}$ | | |
| | | | | | (21.496) | (3.802) | | |
| Constant | -362.518$^{***}$ | -373.517$^{***}$ | -13.010$^{***}$ | -10.639$^{***}$ | 154099.504 | -156451.911$^{**}$ | 92.660$^{***}$ | 100.732$^{***}$ |
| | (-3.510) | (-3.935) | (-12.719) | (-10.521) | (0.824) | (-3.348) | (9.732) | (14.499) |
| Observations | 21,627,723 | 21,627,723 | 12,849,550 | 12,349,123 | 30,795 | 30,795 | 7,779 | 7,779 |
| Adj.$R^2$/Adj. Pseudo $R^2$ | 0.001 | 0.002 | 0.082 | 0.096 | 0.881 | 0.964 | 0.781 | 0.791 |
| *Fixed Effects* | | | | | | | | |
| Loan Origination Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Originator | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Originator x Year | No | Yes | No | Yes | No | Yes | No | Yes |
| Clustered SE | Deal | Deal | Deal | Deal | Deal | Deal | Deal | Deal |

**Table 12**

**Instrumental variable approach: Percentage of no-retention-deals**

This table contains the estimates of the second stage of the two-stage-least square instrumental variable regressions. The instrument is the moving average of the percentage of no-retention-deals by the same originator including all deals other than *d*, issued within in a window surrounding one year before and one year after the issuance of deal *d*. The analyses follow the previous pooled-OLS-regressions. We provide all variable definitions in Appendix B. All regressions are run with originator and time fixed effects (odd numbers) or originator-time fixed effects (even numbers). We include loan level control variables and fixed effects for the year of loan origination in all regressions. Standard errors are clustered on deal level. *t* statistics are presented in parentheses. The signs denote as follows: $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

| | (1) Rating Change | (2) Rating Change | (3) Valuation Change | (4) Valuation Change | (5) NPL | (6) NPL | (7) Time to NPL | (8) Time to NPL | (9) Time in Arrears | (10) Time in Arrears |
|---|---|---|---|---|---|---|---|---|---|---|
| Fitted Retention | 0.023 | 0.052 | 0.068 | 0.075$^{+}$ | -0.020$^{***}$ | -0.020$^{***}$ | 187.532 | 616.640$^{***}$ | -85.563$^{***}$ | -79.725$^{**}$ |
| | (0.990) | (1.481) | (1.467) | (1.713) | (-3.377) | (-3.341) | (0.589) | (11.004) | (-3.574) | (-3.104) |
| Constant | -0.162 | -0.014 | 1.249$^{***}$ | 0.821$^{***}$ | -0.051$^{***}$ | -0.055$^{***}$ | 689.724$^{+}$ | -530.193$^{***}$ | -60.971 | -58.781 |
| | (-1.453) | (-0.508) | (11.413) | (9.389) | (-3.403) | (-4.299) | (1.747) | (-11.876) | (-1.032) | (-1.055) |
| Observations | 5,781,489 | 5,781,489 | 19,812,874 | 19,812,874 | 21,546,160 | 21,546,160 | 13,888 | 13,888 | 569,755 | 569,755 |
| Adjusted $R^2$ | 0.246 | 0.325 | 0.611 | 0.689 | 0.028 | 0.034 | 0.737 | 0.869 | 0.148 | 0.167 |
| Loan Level Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fixed Effects* | | | | | | | | | | |
| Loan Origination Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Originator | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Originator x Year | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| Clustered SE | Deal | Deal | Deal | Deal | Deal | Deal | Deal | Deal | Deal | Deal |

**Table 12 Cont.**

| | (11) Delinquency Amount | (12) Delinquency Amount | (13) NPL Recovery | (14) NPL Recovery | (15) Default Recovery | (16) Default Recovery |
|---|---|---|---|---|---|---|
| Fitted Retention | -2874.615* | -2965.617* | 0.052*** | 0.054*** | 0.011** | 0.009** |
| | (-2.403) | (-2.317) | (5.066) | (5.132) | (2.723) | (2.622) |
| Constant | 1970.735 | 1772.131 | 0.294*** | 0.444*** | -0.001 | -0.026 |
| | (1.314) | (1.108) | (3.295) | (4.648) | (-0.035) | (-0.627) |
| Observations | 465,009 | 465,009 | 470,482 | 470,482 | 105,353 | 105,353 |
| Adjusted $R^2$ | 0.128 | 0.164 | 0.043 | 0.051 | 0.061 | 0.071 |
| Loan Level Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fixed Effects* | | | | | | |
| Loan Origination Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Originator | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Originator x Year | No | Yes | No | Yes | No | Yes |
| Clustered SE | Deal | Deal | Deal | Deal | Deal | Deal |

| | (17) Loss | (18) Loss | (19) Default | (20) Default | (21) EAD | (22) EAD | (23) RR | (24) RR |
|---|---|---|---|---|---|---|---|---|
| Fitted Retention | -603.021 | -513.179 | -0.007+ | -0.005+ | -11,616.475 | -11,017.439+ | 1.225 | 1.988 |
| | (-1.448) | (-1.340) | (-1.855) | (-1.676) | (-1.606) | (-1.831) | (0.486) | (0.801) |
| Constant | -2898.666** | -2774.483** | -0.021*** | -0.020*** | 243104.426 | -18471.509 | 95.773*** | 97.195*** |
| | (-2.670) | (-2.802) | (-4.604) | (-5.120) | (1.320) | (-1.509) | (13.164) | (20.738) |
| Observations | 21,645,699 | 21,645,699 | 18,896,584 | 18,896,584 | 30,798 | 30,798 | 8,115 | 8,115 |
| Adjusted $R^2$ | 0.013 | 0.017 | 0.017 | 0.021 | 0.881 | 0.964 | 0.769 | 0.783 |
| Loan Level Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fixed Effects* | | | | | | | | |
| Loan Origination Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Originator | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Originator x Year | No | Yes | No | Yes | No | Yes | No | Yes |
| Clustered SE | Deal | Deal | Deal | Deal | Deal | Deal | Deal | Deal |