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 24 million quarterly loan observations, we examine the effect of risk retention on bank behavior. We show that retention deals perform better due to improved monitoring effort and workout processes. We find that the probability of rating updates or collateral revaluations is higher for retention loans, and the rating quality is better; retention loans have a lower probability of becoming non-performing, a lower delinquency amount, and a shorter time in arrears. Moreover, non-performing and defaulted retention loans are more likely to recover. Reduced losses for deals with retention are driven by lower default rates, lower exposures at default, and higher recovery rates. 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, moral hazard, monitoring

JEL classification: D82, G01, G18, G21, G28

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1 Introduction

The originate-to-distribute (OTD) business model enabled banks to lend money to borrowers almost without being exposed to default risk because they transfered it immediately to investors. Due to the very short risk exposure, banks lowered their screening and monitoring efforts. Even if regulators by now require that the credit risk assessment for securitized loans corresponds to balance sheet loans (Art. 408 of the Capital Requirement Regulation (CRR)), this only aims to reduce adverse selection at loan securitization, but the originator's behavior *after* securitization is also decisive for the performance of securitized loans. Retaining a fraction of asset-backed securities (ABS) might be crucial to alleviate persisting incentive problems. We test theoretical predictions regarding increased monitoring incentives by evaluating whether bank behavior is more favorable if they have "skin in the game": Do banks treat securitized loans differently – in terms of monitoring or during the workout process – depending on whether they retained a fraction of the deal?

While recent research shows that deals without retention perform worse than deals with retention do (Begley/Purnanandam, 2017), the question of *why* deals with retention show superiror performance, remains unanswered. We first confirm a superior loan performance in the presence of retention by showing that the loss volume is lower for retention loans. To provide insights on the reasons for such superior loan performance, we decompose the effect of retention by investigating the loss components separately: the default indicator, the exposure at default, and the loss given default. To examine the economic channels of improved loan performance, we investigate the effect of retention on monitoring activities for loans securitized in a deal with retention ("retention loans") versus loans 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 and the underlying restructuring arrangements. We evaluate this based on a data set of residential mortgage backed securities (RMBS) from the European Data Warehouse (EDW), which is part of the loan-level initiative of the ECB and consists of more than 24 million quarterly loan observations.

To answer our research question, 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 at a given time. Using originator-time fixed effects and a set of controls, our setting allows us to compare loans securitized by the same originator and with similar loan characteristics at time *t*, but differ only in the affiliation to a deal that is equipped with retention ("retention deal") and without retention ("no-retention deal"). Additionally, we perform a propensity score matching and an instrumental variable (IV) approach to examine the causal effect of retention on our dependent variables.

Investigating the impact of retention on the originators' behavior is crucial because regulators left discretionary freedom in treating securitized loans differently *after* securitization. We provide strong evidence for a reduction of moral hazard in the presence of risk retention by analyzing the originators behavior. We find that originators increase their effort substantially to avoid losses: First, in deals with retention, originators increase monitoring actions. This is indicated by significantly more frequent rating updates and collateral revaluations (both 3 times more likely for retention loans) as well as a higher rating quality, which increases the AUC value 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 58% lower likelihood of becoming non-performing and the delinquency amount is about € 350 less for retention loans. Third, originators with skin in the game are more successful in the workout process of non-performing and defaulted loans. The time in arrears is 12 months lower and the probabilities of recovery from non-performing or default are both 40% higher for retention loans. Our results for loan performance suggest that retention helps to reduce the losses of RMBS loans by about € 112 per loan and year, which is driven by a 1.5 times lower default rate, a € 16,000 decreased exposure at default, and an 11 percentage points higher recovery rate. This results in a substantial loss reduction of around € 1.75 million per year for the average RMBS deal. Overall, we provide evidence that the security design can mitigate agency problems in the securitization market. Our analyses provide detailed information on the changes in the originators' behavior when the originator has skin in the game, resulting in substantially reduced moral hazard. We offer a comprehensive image of the originators' actions in securitization with and without retention.

A potential endogeneity concern is the selection of bad quality loans into the different types of deals, given ample evidence for adverse selection in the pre-crisis US RMBS market. Although there is no evidence for a similar adverse selection problem in the post-crisis EU RMBS market, we address this concern in several ways. First, comparing retention and no-retention loans, we do not find any evidence that banks systematically select less risky loans into retention deals based on *observable* loan characteristics. Second, our sample only consists of high-documentation loans, for which adverse selection based on *unobservables* is less of a concern (Demiroglu/James, 2012; Jiang et al., 2014; Rajan et al., 2015). Third, the selection of bad quality loans for securitizations is prohibited in the EU. Even if we cannot investigate unobservable loan characteristics with EDW data, originators have to consider that regulators have a larger information set: In regulatory audits, regulators get access to internal bank data, so that most "unobservable" loan characteristics become observable. Thus, adverse selection would be easily verifiable for regulators since they can test if the securitized pool is a random draw from the balance sheet loans. Testing for moral hazard, however, is much more difficult: Even if the EU requires that screening and monitoring of credit and counterparty risk is ensured through effective systems for all financial institutions (Art. 79c Capital Requirements Directive (CRD) IV),[1] the intensity of monitoring effort is hardly verifiable. Thus, despite their legal obligations, it is reasonable that originators vary their monitoring effort mainly based on economical considerations. Fourth, to ensure that the effect of retention is indeed causal, we implement an instrumental variable approach. To sum up, our results support the view that we can attribute the more favorable performance of retention loans mainly to higher bank effort in monitoring and during the workout process.

We contribute to the literature on 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, 2019; Hébert, 2018; Daley et al. 2020; Adelino et al., 2019), which also establishes that retention improves incentives by assuring that the originator has skin in the game. Combining pooling, tranching, and retention of the equity tranche is a close approximation of the optimal security design (DeMarzo, 2005; Hartman-Glaser et al., 2012; Vanasco, 2017). Well-designed securitization contracts can improve screening incentives and reduce losses, as well as defaults of tranches (Demiroglu/James, 2012; Malamud et al., 2013; Ghent et al., 2019). However, the amount of retention can signal asset quality to uninformed investors, hence, a compulsory retention amount impedes this signaling opportunity.

[1] This rule does apply to both, securitized and balance sheet loans.

Against this background, a prescribed flat-rate retention can be socially suboptimal due to the information destruction (Leland/Pyle, 1977; Boot/Thakor, 1993; DeMarzo/Duffie, 1999; Hartman-Glaser, 2017; Guo/Wu, 2014; Vanasco, 2017). Moreover, retention seems to be a substitute for reputation and ratings (Hartman-Glaser, 2017; Daley et al., 2020). Chemla/Hennessy (2014) introduce a theoretical model in which the originator's effort depends on the level of equity retention. Since higher retention increases the originators willingness to pay for monitoring activities, it decreases moral hazard. We add to the literature by providing empirical evidence that retention proves to be effective in increasing monitoring effort and decreasing moral hazard in securitizations.

In contrast to the rich theoretical literature, there are few empirical findings on the effect of retention. For the US pre-crisis RMBS market, 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; hereby, 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 line with this finding, mandatory equity retention according to the Dodd-Frank-Act 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). However, it remains unclear how retention affects the performance of individual loans depending on the banks' behavior. We contribute to this strand of the literature by disentangling the effect of retention on loan-level performance. We provide a comprehensive analysis of delinquencies, decompose the losses due to defaults, and analyze the effort to recover non-performing and defaulted loans using loan-level data.

A second related strand of the literature deals with the contribution of ABS to the financial crisis. In the pre-crisis period, many originators securitized 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 decreasing quality of securitized loans, especially if a bank is capital-constrained or performed poorly in terms of negative stock returns. The increased securitization activity with the OTD model deteriorated the lenders' information gathering before loan origination on the one hand, and led to the systematic securitization of worse loans on the other hand

(Berndt/Gupta, 2009; Keys et al., 2010; Titman/Tsyplakov, 2010; Purnanandam, 2011; Nadauld/Sherlund, 2013; Jiang et al., 2014). Moreover, loans securitized after some time on a bank's balance sheet are less risky than are loans securitized within the OTD model. In line with this reasoning, 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 showing that skin in the game harmonizes the interests of originators and investors, which leads to superior loan and deal performance. We provide evidence that skin in the game mitigates moral hazard problems, and therefore supports the restoration of trust in the securitization market, thus helping to resolve the ongoing adverse effects of the financial crisis.

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). While Bubb/Kaufman (2014) provide evidence that discontinuities in the credit scores of securitized loans do not serve as good measures to prove moral hazard in securitizations, moral hazard cannot be rejected for the Italian securitization market (Albertazzi et al., 2017). We, therefore, focus on bank behavior after securitization to analyze moral hazard and provide evidence that retention incentivizes banks to exert higher effort after securitization, resulting in mitigated moral hazard. Second, information asymmetries can be problematic after loan origination and before the securitization decision, indicating that the securitized pool is not a random sample of the originators' balance sheet loans but that the originators use this method to remove undesired exposures from their 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; Adelino et al., 2017; Kara et al., 2019). Nevertheless, some studies find 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 significantly affect loan quality at securitization in the post-crisis European RMBS market. However, we note that this could be a consequence of the regulatory requirement in the EU that the credit risk assessment of securitized loans has to correspond to balance sheet loans. Third, information asymmetries can be problematic after loan securitization between originator and investor, if originators treat securitized loans differently in terms of monitoring effort, modifications, renegotiations, and 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; Adelino et al., 2013; Adelino et al., 2014). We contribute to this literature by showing that the originators' monitoring activities improve not only for balance sheet loans, but also for securitized *retention* loans: Banks exert higher effort in terms of rating updates, collateral revaluations, and rating quality. Furthermore, we provide evidence that retention mitigates delinquencies in terms of the probability of becoming non-performing, delinquency amount and time in arrears, as well as the probability of resolving non-performing loans (NPLs) and defaults.

2 Data

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

2.1 Institutional setting and 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 analyze the composition of a deal's loan pool before investing. In this respect, the EDW database was created with the aim of increasing transparency and restoring confidence in the European ABS market (Trichet, 2011).

In addition, the CRD introduced the minimum retention rules in Article 122a on January 1, 2011. Article 405 (CRR) slightly re-defines minor aspects, and the current version of the retention rules are set in the European framework for securitizations. Since the introduction of the retention rules, the retention requirement is fulfilled if the originator retains "a material net economic interest in the securitization of not less than 5%" of the deal volume. When considering an investment into securitizations, investors located in the EU have to make sure that the respective transaction fullfills the retention requirements; otherwise, EU investors are not allowed to hold the securitization position. However, it is generally possible for European originators to issue securitizations without retention after 2010 that only non-EU investors can purchase. We provide further information and an overview of the different types of retention in the EU and the US in Appendix A.

In Q2/2019, the outstanding European ABS deals amounted to € 1.25 trillion, of which € 684 billion was on RMBS (SIFMA, 2019). The residential RMBS market consists mainly of private-label securitizations since commercial banks are the primary users of the market to transfer their exposures to investors. In European deals, originators of both, retention and no-retention deals usually act as the servicer of a deal, which is true for all deals in our sample. Hence, the originators remain responsible for monitoring activities, renegotiation and restructuring arrangements after securitization. In contrast to the US, restructuring loans after securitization is permitted in the EU and we have information available if a borrower and originator agreed to restructure the loan.

Our data set consists of loan-level data from the EDW database. We collect all quarterly European RMBS deal submissions issued between 2009 and 2017 and track the submissions until the end of 2017. We exclude all loans that have no unique identifier within a deal, a negative time to maturity, or have missing values for at least one of our control variables. Moreover, we only consider deals of originators that issued retention *and* no-retention deals. As we can track loans over time, our final sample consists of 24.9 million loan-quarter-observations of 2.4 million loans in 156 deals.

2.2 Variable measurement

We manually extract all retention information directly from the investor prospectuses. 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. After the introduction of the minimum retention rules, most originators reveal only that the deal fulfills the regulatory requirements; thus, we assume that they choose the legal minimum of 5% (as Flynn et al. 2019 show for the US). For deals issued before 2011, we consider retention as fulfilled only if the retention amount is at least 5% of the deals' nominal value for consistency. If this threshold is not exceeded or there is no retention information available in the prospectuses, then we assign no (qualified) retention. While in 2009 and 2010, only a few deals have retention, the number of deals without retention dropped throughout the introduction of the minimum retention rules in 2011.

Nevertheless, some deals were issued without retention even after 2010. Originators must consider that retention deals are costly because of the potential losses. If an originator wants to avoid these losses, then, on the one hand, the originator can carry out cost-intensive screening and monitoring tasks, such as collecting information from credit bureaus or verifying documents or collateral values. On the other hand, originators can avoid these losses by foregoing EU investors as potential investors, which makes the issuance of new no-retention deals possible after 2010. Table 1 presents the distribution of retention across the sample period.

Table 1 about here

As dependent variables, we use indicator variables for *Rating Updates* and *Collateral Revaluations* of the collateral, *Rating Quality*, Δ*Rating Quality*, an indicator variable for non-performing loans (*NPL*), *Time In Arrears*, *Delinquency Amount*, and indicator variables for delinquency recovery (*NPL 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. Table 2 presents descriptive statistics of the dependent variables. Some values are missing due to data quality, but most occur because some variables are only available in special cases, such as the exposure at default and the recovery rate in case of default. Except for 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 one of our dependent variables, we cannot provide descriptive statistics. The rating is considered optional in the loan-level initiative and is unfortunately not standardized; consequently, each originator submits different rating classes. This makes it hard to compare ratings between deals and very often difficult to interpret the 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, we use the frequency of rating updates as a proxy for monitoring effort on the one hand, and use separate rating fixed effects for each deal when measuring the ability of each deal's rating system to predict future defaults as a proxy for the effort to reduce asymmetric information on the other hand.

As control variables, we use a loan's *Interest Rate* and *Time To Maturity* as measures of credit risk. Additionally, in line with the finalization of the Basel III reforms, we use *Loan To Value* (LTV) as a key figure for real estate-related exposures (BIS, 2017). *Loan Balance* (and the *Original Loan Balance*) is an essential variable for the securitization decision and a proxy for risk concentration (Ghent/Valkanov, 2016). Table 2 provides the summary statistics of the control variables. Loan balances with values of 0 occur for the 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 € 1.55 billion and consists of around 15,700 loans. The average sample loan has an original volume of about € 102,000, an interest rate of roughly 3.3%, and a remaining maturity of 21 years. The loan amount corresponds to about 73% of the collateral value.

3 Empirical strategy

Theory suggests that requiring deals to include retention should harmonize the interests of originators and investors. In particular, the theoretical model of Chemla/Hennessy (2014) predicts that retention reduces moral hazard by incentivizing banks to exert higher monitoring effort. If retention has this desired effect, we should find an improvement in the originators' behavior. We test this prediction and expect retention to increase monitoring effort, decrease delinquencies and defaults, and improve the workout process for a given originator, compared to the originator's actions in a deal without retention. We conduct a *within-originator* analysis to indicate how a given originator treats two loans that differ only in whether the loans are assigned to a retention- or a no-retention deal.

A major challenge is that the originators' actual actions and efforts regarding these lender-borrower-relationships, and therefore the actual monitoring quality, are not observable. Hence, we must use proxy variables for the originators' behavior. First, we investigate moral hazard in the presence of retention, controlling for loan characteristics. As proxy variables for monitoring effort, we analyze the likelihood of rating updates, the likelihood of collateral revaluations, 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. Regarding modifications, renegotiations and the workout process, we examine the time in arrears, the delinquency amount, the likelihood of recovering non-performing and defaulted loans, as well as the frequency and effectiveness of restructuring arrangements. Second, we analyze whether loan characteristics differ at loan securitization depending on retention, which would indicate a selection problem based on observable characteristics. In addition, we address the potential selection problem based on *unobserved* characteristics in several ways: I) We only consider high-documentation loans in our sample, for which adverse selection based on unobservables is less of a concern (Demiroglu/James, 2012; Jiang et al., 2014; Rajan et al., 2015). II) The EU regulation requires that the risk assessment of securitized loans has to correspond to balance sheet loans, which also applies to retention deals and no-retention deals. While we cannot examine possible differences in unobservable characteristics, originators must be aware that regulatory audits, in which the regulator has access to the bank internal data, would reveal such an adverse selection and is therefore unlikely. III) We implement an instrumental variable approach to rule out remaining concerns regarding the selection problem. Third, in addition to analyzing the impact of retention on moral hazard and adverse selection, 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 moral hazard provide a comprehensive image of the effect of retention on bank behavior, resulting in a substantial mitigation of moral hazard. Figure 1 and Table 3 provide an overview of the subsequent analyses.

Figure 1 about here

Table 3 about here

We next describe our empirical strategy to investigate the effect of retention on the originators' behavior and support our findings with the established theoretical argumentation. We consider only deals of originators that issued at least one retention deal and one no-retention deal. We restrict this sample to create a comparison of each originator's loans, which are similar in as many characteristics as possible and only differ in whether it is a retention or no-retention deal, at a given point in time. To control for the unobservable heterogeneity of originators, we include originator-time fixed effects.[2] With this strategy, our analyses reveal the *within*-originator heterogeneity regarding retention loans and no-retention loans, indicating that the behavior differs only depending on whether a loan is assigned to a deal with or without retention. In addition, we use several loan characteristics as control variables.

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

$$Y_{i,t} = \beta_0 + \beta_1 \cdot Retention_d + \delta \cdot Controls_{i,t} + \psi_{t\times o} + \psi_{i,year} \quad (1)$$

The indicator variable $Retention_d$ is our variable of interest and takes the value of 1 if a deal d is a retention deal, and 0 otherwise. Because loans with some characteristics might be treated differently than are others, we add the vector $Controls_{i,t}$, which is a set of loan-level control variables of loan i at time t, consisting of *Time To Maturity, Interest Rate, Loan To Value*, and *Loan Balance*. For all analyses with dependent variables that are euro amounts, we include the nominal amount of *Loan Balance*,[3] otherwise we include the log transformed variable. We provide all variable definitions in Appendix B. Due to the time constant variable of interest – the indicator variable retention – we cannot employ deal fixed effects. Hence, we estimate all regression models using ordinary least squares (OLS) or logit regressions. Originator-time fixed effects, as indicated by $\psi_{t\times o}$, control for the unobserved heterogeneity of originators, which can change over time. We include year-of-loan-origination fixed effects, indicated by $\psi_{i,year}$, since the time of loan origination correlates with a loan beeing a retention loan and we cannot

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[2] Since originators issue deals with assets from only one country in our sample, originator-time fixed effects also control for country- and country-time-specific effects. In addition, we do not need to account for different default regulations since the EU established the Basel III default definitions.

[3] Thus, we regress euro amounts on euro amounts.

rule out the possibility that it also correlates with dependent variables like loan performance measures. The standard errors are heteroskedasticity robust and clustered at deal level for all regressions.

Even if accounting for originator-time fixed effects should eliminate many potential sources of endogeneity, a possible concern is that the assignment of a loan to a retention or a no-retention deal by a given bank is not exogenous, which could lead to systematical differences between retention and no-retention loans. We therefore deal with possible sources of endogeneity in several ways. First, we analyze differences between retention and no-retention loans at the time of securitization, and we find no evidence of systematic selection of riskier loans for no-retention deals, which is plausible because in the EU, the screening of securitized loans has to correspond to balance sheet loans. While investors cannot investigate the unobservable characteristics with EDW data, originators have to take into account that regulators can reveal potential selection based on unobservables in audits since they have access to internal bank data. Second, we perform a propensity score matching for all loan-level analyses, which can reduce the bias due to confounding variables; the corresponding findings are consistent with the results from our main specifications (see Appendix C). Third, we implement an IV approach to infer the causal effect of retention. We describe the construction of the instrument and the corresponding results in Section 7. We construct the instrument following Ashcraft et al. (2019), which indicates the originator's opportunity to securitize loans into no-retention deals instead of retention deals to avoid losses from these loans. The originators could use this opportunity to assign loans with expected poor performance to a no-retention deal and therefore avoid losses from having skin in the game. The greater the percentage of no-retention deals is, the better the originator's expected monitoring is for loans assigned to a retention deal instead, and the better their performance. Ashcraft et al. (2019) show the tranche performance is improved if the originator has other deals available without having skin in the game. However, they do not show *why* tranche performance improves. On the contrary, we provide evidence that the loan-level performance improves because the originator behaves differently if the originator has skin in the game, leading to a reduction of moral hazard. The results of the propensity score matching and the IV approach both confirm our subsequent findings.

4 Skin in the game and moral hazard

Once the originator securitizes a loan into a no-retention deal (and therefore has no skin in the game), the originator has no exposure to the loan's credit risk and therefore no incentive to avoid possible losses (if reputational concerns are ignored). Thus, the originator could refrain from costly checks of credit-worthiness, renegotiations and modifications, as well as recovery and workout attempts. Subsequently, we investigate the originators' behavior in these aspects after a loan is securitized depending on the presence of retention. Since the recognition of undesirable developments (e.g., arrears and defaults) is the necessary condition for the prevention of arrears, we begin our analyses with the banks' monitoring effort.

4.1 Monitoring activities with skin in the game

Having skin in the game, originators have to expect losses due to the ongoing exposure to credit risk and loan defaults. As long as monitoring activities are less costly than the expected losses due to retention are, it is rational for the originator to maintain monitoring activities after securitization to avoid losses. Therefore, we expect originators of retention deals to put more effort into costly monitoring activities. This argument is in line with the model of Chemla/Hennessy (2014), which states that the originators maximum willingness to pay for monitoring effort depends on retention. Since we cannot observe the actual monitoring activities or costs, we use the likelihood of rating updates, likelihood of collateral revaluations, and rating quality as proxy variables for monitoring activities. First, we investigate the likelihood of rating updates. If a loan's rating changes over time, then it could be due to a new assessment of credit risk within the monitoring process. However, we cannot rule out the possibility that the rating changed due to a data failure or a redefinition of the rating scale. While the latter reasons should not improve default prediction systematically, rating quality should improve if the rating update is the result of monitoring actions. Against this background, we test whether updated ratings improve default prediction. Indeed, in 95% [89%] of cases, rating updates improve default prediction significantly (at the 10% [1%] level). Another aspect of monitoring borrowers is the revaluation of the collateral, whicht will often result in a new collateral value. Thus, we investigate the probability of the collateral revaluation. We perform a logit regression of the indicator variables *Rating Updates* and *Collateral*

Revaluation on *Retention* as in Equation 1, with $Y_{i,t} = P(RatingUpdate_{i,t}=1|X_{i,t})$ and $Y_{i,t} = P(CollateralRevaluation_{i,t}=1|X_{i,t})$ as dependent variables.

To conduct the first analysis, we generate an indicator variable *Rating Update*, which takes the value of 1 if the rating of loan *i* at time *t* is different from the rating at time $t-1$, representing a rating update. Analogous to rating updates, we generate an indicator variable *Collateral Revaluation*, which equals 1 if the collateral value changed in the last period. We regress these indicator variables on *Retention* and the set of control variables. We report the results of the effect of retention on the likelihood of rating updates (columns 1 and 2) and collateral revaluation (columns 3 and 4) in Table 4.

Table 4 about here

The coefficients of the variable *Retention* indicate that the likelihood of rating updates and collateral revaluation increase significantly if a deal has retention. This effect is economically very meaningful. The probability of both rating updates and collateral revaluations, is around three times higher for retention loans than for no-retention loans.[4] This finding suggests that the originators' incentives to avoid losses substantially increase in the presence of retention, which is in line with the theoretical arguments.

In a second analysis of monitoring incentives, we investigate the rating quality. If the originator monitors borrowers, then 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 perform a two-level procedure. On the first level, we evaluate each deal's rating system using loan-level data. For this purpose, we calculate the explanatory power of each rating system to predict future defaults. This first-level regression is a logit default prediction, where we estimate the probability of a loan defaulting within the next 12 months using the model in Equation 2.

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[4] As a robustness check, we use the number of rating changes per loan and year as a variation of this analysis. Retention increases the number of rating changes by more than 0.6 changes per year. This result is statistically significant at the 0.1% level. The sample average number of rating changes per year is about 0.25. Evaluating the economic effect of retention, we find that the number of rating updates per year is 2.4 times higher for retention loans.

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

$Default_{i,t+12}$ is an indicator variable equal to 1 if loan *i* defaults within the next four quarters, and 0 otherwise. The vector *CreditRating* considers rating fixed effects based on each deal's rating system. Since loans with some characteristics might be monitored more intensively, we add the vector *Controls* at the first level, which consists of *LoanBalance*, *LoanToValue*, *TimeToMaturity* and *InterestRate.* As we run this regression for each deal separately, it is not possible to include originator-time fixed effects; instead, we add time fixed effects ψ_t to control for the development of rating systems over time due to regulatory influence or macroeconomic effects. We use the area under the receiver operating charachteristics (ROC) curve (AUC) for each deal *d* and time *t* as the measure of $RatingQuality_{d,t}$.[5]

As a variation of this analysis, we study the improvement of a bank's rating system compared to a very simple rating system to create another measure of monitoring effort. We create the naïve rating system, which predicts future defaults based on a set of loan-level characteristics from Equation 1 but omits the interest rate as it is the result of the rating system. We compute the area under the curve of the naïve rating system, and thus the variable $RatingQuality_{d,t,naïve}$, analogously. Afterwards, we generate the surplus of the originators' rating systems' ability to predict future defaults $\Delta RatingQuality_{d,t}$ by subtracting the measures of rating quality (i.e., the AUC values), as in Equation 3.

$$\Delta RatingQuality_{d,t} = RatingQuality_{d,t} - RatingQuality_{d,t,naïve} \tag{3}$$

In the first level, we use loan-level data. Because 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 to 7.3 million observations. We canot provide first-level regression results because there is a regression table for each deal, though we do provide data on the explanatory power of the average deal. The average rating system has an area under the curve of 80.9%, which is, on average, 4.6 percentage points better than the naïve rating system.

[5] As a robustness check, we implement the pseudo-R^2 instead of the AUC as a measure of rating quality (results are available upon request). Overall, these results are economically meaningful and in line with the findings for the AUC. 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, which means that the rating quality improved by about 33%.

In the second level (Equation 4), we relate the *RatingQuality* (or $\Delta RatingQuality_{d,t}$) to the existence of $Retention_d$.

$$\begin{gathered} Y_{d,t} = \gamma_0 + \gamma_1 \cdot Retention_d + \psi_{t \times o} + \varepsilon_{d,t} \\ with\ Y_{d,t} = RatingQuality_{d,t}\ or\ Y_{d,t} = \Delta RatingQuality_{d,t} \end{gathered} \tag{4}$$

In this OLS regression, originator-time fixed effects $\psi_{t \times o}$ control for unobserved originator specific characteristics, and standard errors are clustered at the deal level. The analysis of this second level is based on deal-quarter observations. We provide the results in Table 5. 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 improves by about 6 percentage points, which is equivalent to 8% of the average deals' capability of default prediction.

Table 5 about here

Regarding this analysis, one could argue that the sample consists mainly of deals eligible for the ECB to provide favorable refinancing for the originators. Relevant for the refinancing costs is the riskiness of the deal's tranches. To reduce the reported 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, this concern about the sample selection does not apply.

Summing up, we find that retention is associated with an increase in the likelihood of rating updates, collateral revaluations, and an improved rating quality, all of which are proxies for monitoring effort. These findings imply that originators treat securitized loans differently if they have skin in the game.

4.2 Restructuring and the workout process of NPLs

The next set of analyses refers to the originator's behavior regarding NPLs. First, we look at the effort 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' efforts in recovering non-performing and defaulted loans with restructuring arrangements.

Facing financially distressed borrowers, the originator can try to avoid letting the loan become non-performing. For example, the originator can renegotiate the loan terms or agree to restructuring arrangements, such as by reducing the redemption rate. This could put the borrower in the position to pay off the outstanding loan in good order. The necessary conditions to prevent arrears are the identification of impending financial distress and the willingness to prevent a loan from becoming non-performing. Analogous to the considerations in the previous sections, the originator has incentives to prevent losses and delinquency of borrowers only if the originator has skin in the game. We expect retention to decrease the probability of becoming non-performing *P(NPL=1)*.

To test this expectation, we run OLS and logit regressions according to Equation 1 with the dependent variable $Y_{i,t}$ = *P(NPL=1)*. We infer the indicator variable *NPL* from the account status. It takes the value of 1 if a loan is in arrears and the time in arrears is greater than 30 days. We present the results in Table 6. The coefficient of retention implies that the probability of becoming non-performing is 57% lower for retention loans. The following analyses further investigate the originators' actions once a loan becomes non-performing. Taken as a basis for the following analyses, the sample average of time in arrears, given a loan is non-performing, is 32 months, and the median is 27 months. The more effort the originator puts into identifying financially distressed and delinquent borrowers, and the more willing the originator is to adjust loan terms, the faster the originator can resolve the delinquency on average. As skin in the game should incentivize these actions, we expect retention to decrease the time in arrears. In addition, given that a loan is already non-performing, it is in the interest of an originator with skin in the game to avoid a further increase in the delinquency amount, which could potentially lead to higher losses. The originator can do so by renegotiating and modifying the loan terms, or restructuring the loan. Thus, we expect retention to decrease the average delinquency amount of NPLs. 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. We present the results in Table 6. Retention effectively reduces the time in arrears by more than 12 months. This effect is highly statistically significant and economically meaningful. Retention also decreases the delinquency amount by about € 350. This effect is not due to the different loan size as, first, retention loans are on average larger, and second, we include loan size as a control variable. Regarding the control variables, we observe the plausible effect of riskier loans in terms of LTV, as these tend to be in arrears for a longer period and have a higher delinquency amount.

Table 6 about here

Another measurement of successful actions to avoid losses is the recovery of NPLs. Following loan account statuses over time, we can track if an NPL becomes performing again. For this case, we generate an indicator variable *NPL Recovery*, which takes the value of 1 if an NPL'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 of 0. Similarly, during the workout process a defaulted loan can become performing again, and afterwards, credit terms are fulfilled and the loan is repaid. Analogous to the recovery of NPLs, we introduce an indicator variable *Default Recovery*, which takes the value of 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.[6]

We estimate the recovery of NPLs $Y_{i,t} = P(NPLRecovery_{i,t}=1|X_{i,t})$ and the probability of default recovery $Y_{i,t} = P(DefaultRecovery_{i,t}=1|X_{i,t})$ with a logit regression model based on Equation 1.

Table 7 about here

[6] As a robustness check, we consider loans as recovered from NPL (or default) only if the account status changes from non-performing (defaulted) to performing but not to redeemed. The results remain statistically significant but become economically slightly more pronounced. The results are available upon request.

We provide the results in Table 7. Focusing on the recovery of NPLs, we find a highly significant and economically very meaningful effect of retention on modification and renegotiation incentives, indicating that the probability of recovery is 40% higher for retention loans. The negative signs of the coefficients of *Interest Rate* and *Loan To Value* suggest that riskier loans have a lower probability of recovery. Additionally, if the outstanding amount of the loan is higher, then recovery is a greater challenge. Completing the image, we find evidence that retention also helps to increase the probability of recovery from default by 40% as indicated by the odds ratio. These effects suggest that for retention loans, originators try to maintain costumer-relationships and reconstitute their creditworthiness.

Additionally, to show that the higher probability of recovery from non-performing or default is due to loan modification and restructuring attempts by the originator, we analyze the restructuring arrangements of the loans. While we do not observe that loan restructuring arrangements are generally more likely for retention loans, we find that restructuring arrangement are more effective for retention loans. We analyze the effectiveness with a linear probability model. To do so, we include an interaction term of retention and an indicator variable for having a restructuring arrangement in place in the analyses of recovery from non-performing and defaults (similar to Table 7). The coefficient of this interaction term indicates that the probability of recovery from non-performing increases by 7.9 percentage points ($p<0.01$) and that the probability of recovery from defaults increases by 6.8 percentage points ($p<0.1$) if restructuring arrangements are agreed on for retention loans.[7]

In conclusion, the results in this section present a comprehensive understanding of the economic importance of retention to prevent losses from NPLs. Ultimately, retention helps to reduce credit risk in many ways due to increased effort in the monitoring and workout process. Having shown that retention mitigates moral hazard, we analyze whether selection into securitization for no-retention deals is also a problem by investigating the loan characteristics at securitization.

[7] The results are available upon request.

5 Skin in the game and selection into securitizations

A possible concern is that retention loans and no-retention loans could already have different loan characteristics at the time of securitization. To mitigate this endogeneity problem, first, we included several observable loan characteristics as control variables in the previous regressions. Second, we only considered high-documentation loans, for which a selection based on unobservables is expected to be less of a concern (Demiroglu/James, 2012; Jiang et al., 2014; Rajan et al., 2015). Subsequently, we return to the beginning of the loan securitization process and compare observable loan characteristics of retention loans and no-retention loans, similar to Demiroglu/James (2012) based on equation 5 to analyze the possible selection problem based on observable characteristics.

$$\mathrm{P}(Retention_{i,t} = 1 \mid X_{i,t}) = \beta_0 + \delta \cdot Controls_{i,t} + \psi_{t \times o} + \psi_{i,year} \qquad (5)$$

As in the previous analyses, $Controls_{i,t}$ represents a set of loan-level control variables of loan *i* at time *t*, consisting of *Time To Maturity, Interest Rate, Loan To Value*, and *Loan Balance*. To analyze the loan characteristics at securitization, we include only the first observation of each loan in the subsequent analysis. We do not find evidence that retention loans and no-retention loans differ substantially at securitization (see Table 8).

Table 8 about here

In summary, we find no evidence of systematic selection of riskier loans for securitization, which is not surprising since the selection of bad quality loans for securitizations is prohibited, and we only consider high-documentation loans, for which a selection problem is expected to be less of a concern. This gives additional support to our finding that higher monitoring effort after securitization for retention loans is not based on different loan characteristics that exist prior to 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 find a positive impact of retention on monitoring and during the workout process. Such improved incentives should ultimately lead to better loan performance in terms of lower economic losses. Against this background, we first investigate the effect of retention on loan losses. Afterwards, we decompose this effect to examine the elements of loss. The empirical literature reports that non-securitized loans are of better quality and default less often than securitized loans do (e.g., Ghent/Valkanov, 2016). Similarly, we find that retention is associated with a reduction in losses,[8] 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 by investigating the total loss amount from each loan. As the loss is the product of the default indicator, exposure at default, and loss given default, we disentangle the loss for each of these three factors by analyzing whether there are systematic differences for retention versus 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 at t+1, the *Exposure At Default*, and the *Recovery Rate* as the complement of the loss given default (=1–*RecoveryRate*).

$$\begin{aligned} &Y_{i,t} = Loss_{i,t} \;\; or \;\; Y_{i,t} = P\left(Default_{i,t+1} = 1 \mid X_{i,t}\right) \;\; or \\ &Y_{i,t} = ExposureAtDefault_{i,t} \;\; or \;\; Y_{i,t} = RecoveryRate_{i,t} \end{aligned} \tag{6}$$

To analyze the default rates, we run logit regressions; all other regressions are run as OLS. For the analyses with *Exposure At Default* as the 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* and *Recovery Rate*, we restrict the sample to defaulted loans.

We present the results in Table 9. For deals with retention, the results suggest that the average loss per loan and year is about € 112 (= € 28 per quarter) lower in deals with retention. Decomposing the

[8] Until the introduction of the EU securitization regulation in 2019, there was no rule regarding the overall performance of securitized loans. While the overall loan performance in deals issued after 2018 is now benchmarked against the performance of balance sheet loans, deals issued earlier are not affected by this rule. Hence, the loss reduction effect of retention is of special interest for investing in EU deals issued before 2019 and non-EU deals. Furthermore, regulators faced with the decision to introduce or abolish retention requirements rely on a persuasive evaluation of the desired effects of originators having skin in the game.

mechanism of retention to reduce losses, first, 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.[9] In line with expectations, the results further show that riskier loans in terms of LTV and interest rates are more likely to default. Second, we find that retention has a substantial effect on the exposure at default, which decreases by around € 16,000, controlling for *Original Loan Balance*. Third, the slightly significant coefficient of the recovery rate suggests that retention may have a large positive impact on the recovery rate, as well (about 11 percentage points). We conclude from these findings that not only is the avoidance of defaults more effective in retention deals, but also that once a loan defaults, having skin in the game provides incentives to the originator to carry out a cost-intensive workout process to avoid final losses. More precisely, in the face of extremely likely losses, the originator tries to reduce them, such as through a more successful foreclosure or examination of future recovery payments.

Table 9 about here

7 IV approach

To infer the causal effect of retention, we construct an instrument analogous to Ashcraft et al. (2019). While they provide evidence for the impact of skin in the game on the performance of commercial mortgage backed securtities (CMBS) deals on tranche level, we analyze the impact of skin in the game on the performance and originators' behavior for RMBS deals at the loan level as in the previous sections. The results of the OLS/logit regressions and the propensity score matching (see Appendix C) indicate that retention loans are less exposed to moral hazard and perform better, and these findings hold after controlling for loan characteristics, year of loan origination fixed effects, and originator-time fixed effects.

[9] 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, we find that retention and loan size are slightly negatively correlated.

Although we, first, analyze only high-documentation loans and, second, we do not find substantial differences between retention loans and no-retention loans at the time of securitization, one might argue that there might still be endogeneity concerns; for example, the assignment decision might be driven by unobservable loan characteristics such as soft information 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, then the OLS/logit results might be biased. Against this background, our performance results could be explained by two 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* issued at time *t*. The IV, analogous to Ashcraft et al. (2019), 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*. We adopt the variation of the "access" to no-retention deals across time and originators, which we measure with the instrument. Even though the percentage of new no-retention deal issues diminishes over time due to the introduction of the minimum retention rules in 2011, we can still observe the behavior and performance of earlier issuances. The effect, which we estimate using 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 is, the better the originator's monitoring of loans assigned to a retention deal instead will be, 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 has retention; however, it is not correlated with our dependent variables via unobserved factors. We employ the same setting as for our 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.[10] Table 10 shows the second stage results of the IV regressions of our loan-level analyses. For the first stage we find that the F-values are at least 26.4, which suggests that our instrument is very strong in all specifications.[11] We find that the signs of the coefficients from the IV setting remain the same as from our OLS regressions for all analyses, and in most cases the results remain statistically significant. Overall, the IV results confirm the findings of the OLS/logit regressions and of the propensity score matching, indicating that retention has a beneficial causal impact on the originator's behavior.

Table 10 about here

8 Conclusion

The theoretical and empirical literature indicate that agency problems with securitized loans lead to a different treatment compared to balance sheet loans. Theoretical literature also suggests that a lack of skin in the game induces moral hazard and that retention mitigates this problem by increasing the originators' monitoring effort (Chemla/Hennessy, 2014). We test this prediction and show that a proper security design can mitigate agency problems along the credit process substantially. Against the background that the current regulation does rather focus on reducing adverse selection than moral hazard, we show that moral hazard is an important driver of poor loan performance if there is no harmonization of interests, meaning that originators do not have skin in the game. First, we show that retention increases monitoring effort, resulting in a higher probability of rating updates and collateral revaluations, as well as higher rating quality. Second, we show that originators prevent retention loans from becoming non-

[10] 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 confounding the fixed effects and our instrument.

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

performing. We not only provide evidence that the probability of becoming non-performing decreases in retention deals, but also that the delinquency amount and the time in arrears decrease. Third, a recovery of NPLs and defaulted loans is significantly more likely if they are part of a retention deal since restructuring arrangements are more effective in these deals. These findings suggest that retention substantially reduces moral hazard. Fourth, we find that retention loans and no-retention loans hardly differ in terms of riskiness at the time of securitization, indicating that the banks' behavior *after* securitization is decisive for the difference in losses. Fifth, these improved originator incentives 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 trust in the securitization market.

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 the security design can mitigate agency problems in the securitization market substantially. In fact, our analyses provide detailed information on the type and magnitude of changes in the originators' behavior. We offer a comprehensive image of the benefits of retention – providing insights into how ABS should be designed to ensure trust and proper actions. To facilitate the effectiveness of the retention mechanism, regulators should simplify the access to this crucial information by establishing a database, including the retention type, the retention amount and the retaining entity since the investors currently have to search for the retention information in the deal prospectus manually. This database could, e.g., be managed by the securitization reposities of the loan-level initiative.

While we show that retention improves the effort compared to the absence of retention, due to data restrictions, it remains unknown whether this level of effort is comparable to the effort that an originator would take for balance sheet loans. Future research could thus analyze how a given originator, at a given point in time, treats three loans that are equal in all characteristics, except that one remains on the balance sheet, one is securitized in a no-retention deal, and one in a retention deal.

Appendix A. Regulatory retention rules

The EU has five permitted retention types, which we briefly describe below. Equity retention is the retention of the first loss piece and, if essential to reach 5% of the nominal value, 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 (for revolving securitizations only). For deals, in which the number of securitized exposures is at least 100, random selection is the retention of 5% randomly selected exposures, which would have been securitized otherwise. First loss retention is the retention of at least 5% of every securitized exposure.

For comparison, in the US the introduction of risk retention was announced in the Dodd Frank Act in 2010 and specified by the SEC in December 2014. Besides vertical and horizontal slice retention, the US permits a linear combination of them, L-shaped retention. However, the EU decided against integrating L-shaped retention into the regulation since it is more complicated to implement (EBA, 2016). In addition to the differences in the permitted retention types, there exist other distinctions between the EU and US retention rules. In the US, the fair value of the deal is relevant for the calculation of the retention amount, while the rules in the EU refer to the deal's nominal value. In the absence of market prices, the fair value approach allows for valuation flexibility. However, the disclosure requirements are stricter in the US, such as regarding the disclosure of risk parameters. It is noteworthy that the retention requirements in the US exclude qualified residental mortgages. For the definition of qualified residential mortgages, which account for many deals in the US market, see Section 15G of the Dodd Frank Act (Dodd Frank Act, 2010; SEC 2014; Krahnen/Wilde, 2018).

Appendix B. Variable definitions

Variable	Description	EDW Variable AR
CollateralRevaluation	Indicator variable equal to 1 if a loan's collateral value changes between t and t+1	136
Default	Indicator variable equal to 1 if a loan will default at t+1	166
DefaultRecovery	Indicator variable equal to 1 if a loan is in default at t and will become performing or be redeemed at t+1	166
DelinquencyAmount	Maximum volume in arrears given a loan is delinquent (in €)	169
ExposureAtDefault	Outstanding balance at t if a loan will default at 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 1 if a loan status is non-performing and the time in arrears is greater than 30 days	166
NPLRecovery	Indicator variable equal to 1 if a loan is non-performing at t and will become performing or will be redeemed at t+1	166
OriginalLoanVolume	Loan volume at loan origination	66
RecoveryRate	Cumulative recoveries within 2 years after default divided by default volume	177, 181
RatingQuality	Deal's rating system's ability to predict defaults within the next 12 months (AUC or pseudo R^2, measured in %)	17
ΔRatingQuality	Surplus of a deal's rating system's ability to predict defaults within the next 12 months compared to a naïve rating system (measured in %-points)	17
RatingUpdate	Indicator variable equal to 1 if a loan's rating changes between t and t+1	17
Retention	Indicator variable equal to 1 for retention loans (loans securitized in a deal with retention) and retention deals	-
TimeInArrears	Number of months a loan is delinquent (conditional on delinquency)	1, 57, 166
TimeToMaturity	Number of months until loan maturity	56

Note: Variable names "AR" and the 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 analogous to all previous loan-level analyses. We match loans by their one nearest neighbor (with replacement), resulting from all 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 Update	0.1211	0.0642	0.0569	27.54
Collateral Revaluation	0.4816	0.4585	0.0239	12.52
NPL	0.0230	0.0383	-0.0153	-63.72
Time in Arrears	28.24	29.27	-1.04	-0.97
Delinquency Amount	1250	2945	-1695	-3.40
NPL Recovery	0.3160	0.2352	0.0808	27.3
Default Recovery	0.0307	0.0158	0.0148	6.03
Loss	15.41	55.57	-40.16	-9.42
Default	0.091	0.123	-0.0316	-5.86
EAD	150,753	194,280	-43,526	-0.76
RR	91.97	58.73	33.24	3.87

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Table 1
Distribution of retention observations over time

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

Panel A: 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: Observations of loans outstanding							
	2012	2013	2014	2015	2016	2017	Total
No-Retention Loans	161,924	1,823,559	1,870,406	1,576,689	1,199,716	491,459	7,123,753
Retention Loans	222,727	3,108,006	3,629,352	4,358,137	4,347,760	2,146,168	17,812,150
Total	384,651	4,931,565	5,499,758	5,934,826	5,547,476	2,637,627	24,935,903

Table 2

Descriptive statistics of the dependent and control variables

This table presents the summary statistics of our dependent and control variables. N refers to the number of quarterly loan observations; for rating quality (and Δrating quality), N represents deal-level observations. Delinquency amount, loss and exposure at default are measured in Euro, time in arrears is measured in months. Rating update, collateral revaluation, non-performing loan (NPL), default, NPL recovery and default recovery are binary indicator variables. The recovery rate and rating quality are measured in percent, Δrating quality is measured in percentage points. Regarding selection into securitization, we analyze differences with respect to several loan variables, which we use as controls in the other sections; the corresponding descriptive statistics can be found below. We provide all variable definitions in Appendix B. To account for outliers, we winsorize the variables at the 99.5% level.

	N	Mean	SD	Min	q50	Max
Section 4.1 Monitoring after Securitization						
Rating Update (0/1)	6,532,858	0.1	0.3	0	0	1
Collateral Revaluation (0/1)	22,652,021	0.4	0.5	0	0	1
Rating Quality (%)	407	80.93	8.09	60.32	81.35	98.21
ΔRating Quality (%-p)	407	4.57	7.45	-8.75	2.08	29.18
Section 4.2 Restructuring and Workout Process of NPLs						
NPL (0/1)	24,935,903	0.000	0.2	0	0	1
Time in Arrears (months)	201,479	31.96	22.78	1	27.37	104.77
Delinquency Amount (€)	201,347	1482	13,230	0	509.28	2,945,756
NPL Recovery (0/1)	492,679	0.3	0.5	0	0	1
Default Recovery (0/1)	119,223	0.0	0.2	0	0	1
Section 5 Loan Characteristics at Securitization						
Interest Rate, Loan Balance, Loan to Value, Time to Maturity; see *Control Variables* below						
Section 6 Losses and Decomposition of Losses						
Loss (€)	24,826,395	49.2	3,128.7	0	0	616,470
Default (0/1)	24,908,897	0.001	0.1	0	0	1
Exposure at Default (€)	33,061	150,055	557,303	0	102,000	11,666,525
Recovery Rate (%)	10,054	88.5	31.2	0.0	100	100
Control Variables						
Interest Rate (%)	24,935,903	3.3	1.7	0	3.7	7
Loan Balance (€)	24,935,903	102,023	74,505.6	0	89,500	479,006
Orig. Loan Vol. (€)	24,935,903	120,449	81,622.7	3500	104,000	535,000
Loan to Value (%)	24,935,903	72.8	33.0	1.7	73.6	143
Time to Maturity (month)	24,935,903	253.0	112.0	9.0	258.0	990

Table 3

Overview of dependent and key variables and their purpose

Section	Purpose / Proxy for	Variable
4.1	Monitoring after Securitization	Rating Update Collateral Revaluation Rating Quality Δ Rating Quality
4.2	Restructuring and Workout Process of Non-Performing Loans	NPL Time in Arrears Delinquency Amount NPL Recovery Default Recovery
5	Loan Characteristics at Securitization	Interest Rate Time to Maturity Loan to Value Loan Balance
6	Losses and Decomposition of Losses	Loss Default Exposure at Default Recovery Rate

Table 4

Monitoring effort: Rating update and collateral revaluation

This table contains the estimates of logit regressions. Columns (1) and (2) refer to the analysis of the probability of rating updates 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 separate 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 at the deal level. *t* statistics are presented in parentheses. Statistical significance is denoted as follows: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Rating Update	(2) Rating Update	(3) Collateral Revaluation	(4) Collateral Revaluation
Retention	1.302***	1.330***	1.031*	1.165*
	(3.484)	(3.653)	(2.418)	(2.387)
Interest Rate	-0.001	-0.091**	0.095*	0.124**
	(-0.031)	(-2.654)	(2.335)	(3.185)
Log Loan Balance	0.470	-0.053	-0.209**	-0.311***
	(1.624)	(-1.569)	(-2.815)	(-5.134)
Loan to Value	-0.005	0.004***	0.014***	0.014***
	(-1.011)	(3.973)	(3.928)	(4.087)
Time to Maturity	-0.002*	-0.000	0.001**	0.002***
	(-2.032)	(-0.869)	(2.638)	(3.533)
Constant	-9.560***	7.956***	4.210***	1.275
	(-5.439)	(9.783)	(5.489)	(1.113)
Observations	6,321,830	5,736,502	22,629,943	21,192,607
Adj. Pseudo R^2	0.391	0.451	0.622	0.650
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 5

Rating quality

The table contains the estimates of OLS regressions, in which the dependent variable represents the rating quality (Equation 2). Columns (1) and (2) refer to the quality of the actual rating system. Columns (3) and (4) refer to the surplus of the rating system over a naïve rating system. Control variables are included at the 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 on 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 at the deal level. *t* statistics are presented in parentheses. Statistical significance is denoted as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1)	(2)	(3)	(4)
	Rating Quality	Rating Quality	ΔRating Quality	ΔRating Quality
Retention	0.061***	0.053***	0.084***	0.086***
	(10.332)	(13.435)	(12.130)	(22.066)
Constant	0.753***	0.667***	0.045***	-0.092***
	(128.374)	(22.943)	(6.467)	(-4.737)
Observations	407	407	407	407
Adj. R^2	0.622	0.606	0.661	0.552
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 6

Preventing and treating non-performing loans

This table contains the estimates of OLS regressions. Columns (1) and (2) refer to the analysis of the probability of becoming non-performing, (3) and (4) refer to the time in arrears given a loan is non-performing and (5) and (6) 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 at the deal level. *t* statistics are presented in parentheses. Statistical significance is denoted as follows: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) NPL	(2) NPL	(3) Time in Arrears	(4) Time in Arrears	(5) Delinquency Amount	(6) Delinquency Amount
Retention	-0.540*	-0.537*	-12.816***	-12.209***	-284.862	-351.280*
	(-2.307)	(-2.234)	(-3.523)	(-3.358)	(-1.549)	(-2.112)
Interest Rate	0.147***	0.145***	0.805**	0.745*	33.962	42.376
	(5.024)	(5.035)	(2.629)	(2.599)	(1.117)	(1.409)
Log Loan Balance	0.134***	0.131**	-1.644***	-1.655***		
	(3.397)	(3.167)	(-4.282)	(-4.564)		
Loan Balance					0.015***	0.015***
					(5.264)	(5.453)
Loan to Value	0.016***	0.017***	0.122**	0.124**	1.200	3.922*
	(4.674)	(4.500)	(2.609)	(2.768)	(0.532)	(1.978)
Time to Maturity	-0.001*	-0.001*	-0.001	-0.001	-5.627***	-5.827***
	(-2.134)	(-2.475)	(-0.082)	(-0.178)	(-4.167)	(-4.153)
Constant	-8.341***	-8.957***	21.492***	27.898***	2949.55**	4243.14***
	(-10.211)	(-11.965)	(3.543)	(3.851)	(3.307)	(5.359)
Observations	24,903,628	24,903,628	201,443	201,443	201,347	201,347
Adj. R^2	0.076	0.080	0.486	0.556	0.091	0.144
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

Table 7

Restructuring and modification

This table contains the estimates of logit regressions analyzing the recovery probabilities. Columns (1) and (2) refer to the recovery of NPLs, 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 at the deal level. *t* statistics are presented in parentheses. Statistical significance is denoted as follows: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) NPL Recovery	(2) NPL Recovery	(3) Default Recovery	(4) Default Recovery
Retention	0.316^{***}	0.338^{***}	0.373^{*}	0.338^{+}
	(5.194)	(5.502)	(2.330)	(1.827)
Interest Rate	-0.069^{***}	-0.067^{***}	0.039	0.020
	(-7.649)	(-7.084)	(0.360)	(0.188)
Log Loan Balance	-0.040^{*}	-0.042^{*}	-0.068	-0.087^{*}
	(-2.294)	(-2.498)	(-1.474)	(-2.223)
Loan to Value	-0.005^{***}	-0.005^{***}	-0.009^{***}	-0.008^{***}
	(-4.168)	(-4.423)	(-3.716)	(-3.340)
Time to Maturity	0.000	0.000	0.002^{*}	0.002^{*}
	(0.177)	(0.647)	(2.137)	(2.210)
Constant	-1.595	-0.931	-2.094	-1.350
	(-1.280)	(-0.723)	(-1.360)	(-1.364)
Observations	492,284	491,887	65,236	64,868
Adj. Pseudo R^2	0.040	0.046	0.098	0.110
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

Selection based on loan characteristics

Subsequently, we present results of logit regressions (Equation 5), in which retention is the dependent variable. We provide all variable definitions in Appendix B. Column (1) refers to the regressions with originator and time fixed effects, column (2) to regressions with originator-time fixed effects. We include fixed effects for the year of loan origination in all regressions. Standard errors are clustered at the deal level. *t* statistics are presented in parentheses. Statistical significance is denoted as follows: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Retention	(2) Retention
Interest Rate	-0.003 (-0.031)	-0.041 (-0.449)
Log Loan Balance	-0.025 (-0.370)	0.084 (1.172)
Loan to Value	0.005 (1.606)	0.000 (0.090)
Time to Maturity	0.002* (2.036)	0.001 (1.378)
Constant	0.474 (0.295)	0.757 (0.469)
Observations	2,440,207	1,807,146
Adj. Pseudo R^2	0.325	0.396
Fixed Effects		
Loan Origination Year	Yes	Yes
Originator	Yes	Yes
Year	Yes	Yes
Originator x Year	No	Yes
Clustered SE	Deal	Deal

Table 9

Decomposition of losses

This table contains the estimates of OLS and logit regressions (Equation 1). Columns (1) and (2) refer to the analysis of the loss amount, columns (3) and (4) refer to the default status at t+1 (logit), columns (5) and (6) refer to the exposure at default (EAD), and columns (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 a 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 at the deal level. t statistics are presented in parentheses. Statistical significance is denoted 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	-29.524*	-27.989*	-0.433*	-0.411*	-12,391.7	-16,560.2*	11.559^{+}	10.949
	(-2.196)	(-2.122)	(-2.234)	(-2.113)	(-0.997)	(-2.291)	(1.711)	(1.651)
Interest Rate	2.997*	3.436*	0.241***	0.230***	734.98	-5,429.31***	0.268	0.229
	(2.081)	(2.204)	(7.096)	(6.891)	(0.399)	(-7.121)	(0.891)	(0.899)
Log Loan Balance	23.608**	24.278**	0.092^{+}	0.085			-0.972	-1.096
	(3.135)	(3.129)	(1.751)	(1.539)			(-1.621)	(-1.520)
Loan to Value	0.202*	0.188*	0.025***	0.026***	290.90***	403.31***	0.004	0.001
	(2.570)	(2.401)	(8.126)	(7.052)	(3.486)	(4.215)	(0.396)	(0.051)
Time to Maturity	0.001	0.001	-0.001	-0.001	118.08***	135.58***	0.005	0.003
	(0.055)	(0.092)	(-1.039)	(-1.376)	(4.161)	(5.649)	(0.854)	(0.702)
Original Loan Volume					0.501***	0.160***		
					(21.335)	(3.962)		
Constant	-333.690***	-347.818***	-13.277***	-10.835***	152,764.7	-155,345.7**	92.958***	99.443***
	(-3.528)	(-3.968)	(-12.836)	(-10.601)	(0.819)	(-3.357)	(10.442)	(16.457)
Observations	24,801,006	24,801,006	15,552,589	14,761,628	33,058	33,058	8,365	8,365
Adj.R^2/Adj. Pseudo R^2	0.001	0.002	0.082	0.096	0.885	0.964	0.783	0.793
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 10

Instrumental variable approach: Percentage of no-retention deals

This table contains the estimates of the second stage of 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 OLS-regressions. We provide all variable definitions in Appendix B. We run all regressions 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 at deal level. *t* statistics are presented in parentheses. Statistical significance is denoted as follows: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Rating Update	(2) Rating Update	(3) Collateral Revaluation	(4) Collateral Revaluation	(5) NPL	(6) NPL	(7) Time in Arrears	(8) Time in Arrears
Fitted Retention	0.025	0.050	0.070	0.078^{+}	-0.015^{**}	-0.014^{**}	-25.103^{***}	-24.550^{***}
	(1.044)	(1.438)	(1.578)	(1.843)	(-2.977)	(-2.887)	(-5.880)	(-5.879)
Constant	-0.157	-0.014	1.290^{***}	0.849^{***}	-0.051^{***}	-0.061^{***}	20.472^{*}	20.367^{+}
	(-1.432)	(-0.505)	(12.073)	(10.670)	(-3.592)	(-5.187)	(2.129)	(1.936)
Observations	6,526,992	6,526,992	22,630,706	22,630,706	24,905,049	24,905,049	201,443	201,443
Adjusted R^2	0.247	0.328	0.623	0.698	0.019	0.020	0.454	0.525
First Stage F-test	26.5	26.4	258.6	261.9	261.4	266.5	290.6	282.2
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

Table 11 Cont.

	(10) Delinquency Amount	(11) Delinquency Amount	(12) NPL Recovery	(13) NPL Recovery	(14) Default Recovery	(15) Default Recovery
Fitted Retention	-887.669**	-975.119***	0.058***	0.061***	0.011**	0.009**
	(-3.204)	(-3.592)	(6.147)	(6.145)	(2.787)	(2.814)
Constant	3,380.95***	655.540	0.288**	0.449***	-0.002	-0.024
	(5.211)	(0.980)	(3.269)	(4.749)	(-0.049)	(-0.566)
Observations	201,347	201,347	492,286	492,286	109,489	109,489
Adjusted R^2	0.091	0.144	0.044	0.050	0.063	0.073
First Stage F-test	256.1	253.9	258.7	256.3	352.5	328.7
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

	(16) Loss	(17) Loss	(18) Default	(19) Default	(20) EAD	(21) EAD	(22) RR	(23) RR
Fitted Retention	-28.095*	-23.675+	-0.005+	-0.004	-9,561.59	-11,027.26*	1.669	2.284
	(-2.017)	(-1.793)	(-1.664)	(-1.455)	(-1.511)	(-1.978)	(0.682)	(0.938)
Constant	-334.317***	-350.817***	-0.021***	-0.020***	239,435.47	-19,299.77	104.444***	105.747***
	(-3.540)	(-3.977)	(-4.696)	(-5.131)	(1.303)	(-1.639)	(11.727)	(12.441)
Observations	24,801,006	24,801,006	21,999,440	21,999,440	33,061	33,061	8,365	8,365
Adjusted R^2	0.001	0.002	0.016	0.018	0.885	0.964	0.774	0.786
First Stage F-Test	258.8	263.9	252.9	255.6	620.5	602.3	123.5	114.7
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

Figure 1

Scope of analyses

This figure presents the credit process over time. Since we observe loans after securitization, the grey area indicates the scope of the analyses. We begin the analyses with the monitoring effort (Section 4.1). Afterwards we analyze the restructuring and workout process of non-performing loans (4.2). Then we rule out that retention loans are already different from no-retention loans at securitization (5). Finally, we analyze and decompose the losses in the presence of retention (6).