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Securitization and Credit Quality in the European Market

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Abstract

We assess the effect of securitization activity on relative credit quality employing a uniquely detailed dataset from the euro-denominated syndicated loan market. We find that at issuance, based on observable characteristics, banks do not seem to select and securitize loans of lower credit quality. Following securitization, the credit quality of borrowers whose loans are securitized deteriorates more than those in the control group. We find that poorer performance by borrowers of securitized loans seems to be connected to banks' reduced monitoring incentives. Our results are supported by two additional methodologies and robust to controlling for predetermined borrower-lender matching.

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1 Introduction

Banks generate proprietary information and tend to have superior knowledge on the credit quality of the loans they originate. As a result, banks might have an incentive to securitize loans of lower credit quality to unsuspecting investors (Gorton and Pennacchi, 1995). Largely for this reason, securitization has been perceived as a major contributing factor to the 2007-2009 financial crisis (Financial Crisis Inquiry Commission, 2011).

Most of recent empirical evidence on the impact of securitization is United States (US) based and focuses on the mortgage markets. It suggests that prior to the financial crisis banks securitized riskier mortgages (Krainer and Laderman, 2014; Elul, 2015), and that securitization led to poorer quality mortgages (Purnanandam, 2011; Keys et al., 2011). Evidence on the effect of securitization on the corporate loan market is more limited and its findings are contradictory. A number of recent studies find that credit quality of securitized corporate loans are no different than non-securitized loans (Shivdasani and Wang, 2011; Benmelech et al., 2012; Wang and Xia, 2015). In contrast, Bord and Santos (2015) find that securitization led to poorer quality corporate loans.

We contribute to this latter literature by providing the first evidence on the European corporate loan market. The euro-denominated collateralized loan obligations (CLO) market, is a good laboratory to assess the impact of securitization on credit quality on an alternative institutional setting as there are significant differences between the US and European securitization markets. Firstly, the growth of the European securitization has been relatively recent and swift (Kara et al., 2016). It started timidly in the late 1990s, and developed significantly only from 2004 to 2007. On the contrary, in the US the development of securitization markets has been much more continuous over time since the late 1960s. The sudden appearance of securitization in Europe allows for a clearer assessment of its effects on the banking behavior and the financial system. Secondly, unlike in the US the development of the securitization market in Europe has not been driven by government-sponsored institutions such as the Fannie Mae and Freddie Mac. Therefore our results cannot be ascribed to the impact of government intervention via such institutions.

We also contribute to the literature using a novel dataset obtained directly from securitization trustees operating in the European Union (EU). We construct our dataset by getting access to the portfolios of the majority of euro-denominated CLOs so we are able to form a representative picture of the market. Our detailed loan level dataset allows us to distinguish among all syndicated loans, those that were eventually securitized.

In practical terms, we contrast the credit performance of non-financial companies whose loans are securitized versus non-financial companies whose loans are not securitized. Loans extended to these companies, headquartered in the euro area, are granted by euro-area banks between 2005 and 2007. We track changes in borrowers' credit quality as measured by expected default frequencies (*EDF*) after issuance. We then examine the link between future changes in *EDF* and loan securitization controlling for a set of loan, borrower and lender characteristics. As a complementary methodology, we also use propensity score matching to compare the credit risk of corporates whose loans which, prior to securitization, were very similar.

We find that at loan origination, based on observable characteristics, banks do not select and securitize corporate loans of lower credit quality. Following securitization, the credit quality of borrowers whose loans are securitized deteriorates by more than those in the control group. Distinguishing between collateralized and uncollateralized loans, we find that poorer performance by companies with securitized loans is linked to banks' reduced monitoring incentives. Our findings are robust to the use of an instrumental variable to control for possible predetermined borrower-lending matching.

The remainder of the paper is organized as follows: Section 2 briefly reviews and draws hypotheses from the related literature. Section 3 describes the data sources and explains the empirical methodology used in the analysis. The results of estimations are presented and discussed in Section 4. Robustness checks are conducted in Section 5 and Section 6 concludes.

2 Literature and Hypotheses

There is significant evidence from the US suggesting that banks that resorted more intensively to securitization activity in the years prior to the crisis relaxed their lending standards more aggressively than other institutions (Keys et al., 2011; Purnanandam, 2011; Dell'Ariccia, 2012; Nadauld and Weisbach, 2012). There is also related evidence linking securitization activity and increases in bank risk-taking (Instefjord, 2005; Goderis et al., 2007; Haensel and Krahnen, 2007), and systemic risk (Wagner, 2007; Krahnen and Wilde, 2008; Michalak and Uhde, 2013; Brunnermeier and Sannikov 2014).[1] Recent results also suggest that banks securitized their ex-ante riskiest mortgages, and that delinquency rates for securitized mortgages were higher than for non-securitized mortgages (Krainer and Laderman, 2014; Elul, 2015).

In contrast, other studies do not find evidence suggesting that securitization led to riskier lending activities (Shivdasani and Wang, 2011 for leveraged buyouts; Casu et al., 2013 for overall bank risk; Albertazzi et al., 2015 for the Italian market). There is also some earlier literature that underlines the potential benefits of securitization smoothing out risks among many investors (Duffie, 2008), improving banks' ability to manage credit risk (Cebenoyan and

[1] There is also evidence showing that securitization inhibits distressed borrowers' loan renegotiations (Piskorski et al., 2010).

Strahan, 2004) and supporting banks' profitability (Jiangli et al., 2007). For the mortgage market, looking at the pre-crisis period, Ambrose et al., (2005) show that in the US securitized mortgages experienced lower ex-post defaults than those retained by banks.

More closely related to our paper, there is recent empirical work examining the performance of corporate loans in the US after they have been securitized. Some of these studies find that the credit quality of securitized corporate loans is not worse than that of non-securitized loans (Shivdasani and Wang, 2011; Benmelech et al., 2012; Wang and Xia, 2015).[2] Although they have similar findings, these studies have slightly different approaches. Shivdasani and Wang (2011) and Wang and Xia (2015) rely on measurements based on banks' securitization activity by their use of CDO funding while Benmelech et al., (2012) compare the performance of securitized and non-securitized loans originated by the same bank. Bord and Santos (2015) restricted the comparison to loans originated by the same bank and show inferior credit performance for securitized loans following securitization.

Building on this latter literature, in this paper we analyze whether banks securitized their lower quality euro-denominated corporate loans in the build up to the 2007-2009 financial crisis. Information asymmetries on the credit quality of borrowers between originating banks and purchasers of CLOs provide banks with the initial opportunity to do so as originators are likely to have more information about borrowers than the buyers of the CLOs. This is either because they usually have particular expertise on certain sectors, or because they have a lending relationship with the borrower that allows them to collect proprietary information over time. From an

[2] Benmelech et al., (2012) report some evidence of under-performance for securitized loans originated between 2005 and 2007 although they suggest that this is not consistent across samples, performance measures, and horizons.

investor's perspective, a related argument is that even sophisticated investors might have neglected tail risks (Gennaioli et al., 2012).

The credit cycle is also likely to play a significant role in this setting. During good states of a credit cycle investors might be more willing to acquire riskier securities. It could also be that during credit expansions it is more difficult for investors to assess the true value of information intensive securities such as CLOs (Demyanyk and Van Hemert, 2011; Dang et al., 2012; Santos, 2015).

Banks might have an incentive to securitize only those loans of better credit risk to *signal* the quality of the securities (Greenbaum and Thakor, 1987; DeMarzo, 2005; Instefjord, 2005). Banks may also have an incentive to securitize less risky loans if the objective is to increase their risk profile for a given level of capital (Calem and LaCour-Little, 2004). Maintaining their long-term reputational capital in the securitization market might also induce banks to sell their loans of relatively better quality (Albertazzi et al., 2015). In short, the following *signaling* hypothesis would suggest that, based on observables at the time of issuance, originating banks would be securitizing loans of those borrowers whose credit risk is lower:

H1. At issuance companies whose loans are securitized are of better credit quality than, otherwise similar, companies whose loans are not securitized.

After securitization, originating banks might have fewer incentives to monitor borrowers as loans are passed on to outside investors. As a result, over time borrowers of securitized loans would perform worse than borrowers of non-securitized loans as the originating bank would monitor securitized borrowers less intensively (Petersen and Rajan, 2002). Supporting this view, some studies associated loan sales and securitization to looser credit monitoring (Gorton and Pennacchi, 1995; Duffee and Zhou, 2001; Morrison, 2005; Parlour and Plantin, 2008; Chiesa, 2008; Kamstra et al., 2014; Wang and Xia, 2015). We aim to test these arguments with the following *monitoring* hypothesis:

H2. Over time companies whose loans are securitized perform worse than companies whose loans are not securitized due to banks' reduced monitoring incentives.

First, we examine whether there is a difference in the performance of borrowers of securitized loans. Second, to test the *monitoring* hypothesis we track and compare the ex-post credit risk of borrowers of securitized loans versus borrowers of non-securitized loans. Further, we examine those loans for which bank monitoring may have a more significant bearing on borrowers' performance. We conjecture that collateralized loans, where assets are pledged to the bank by the borrower, do not require as much monitoring as uncollateralized ones (Bester, 1985; Cerqueiro et al., 2015). This is because the borrower, having her assets at stake, would be less likely to engage in risk-shifting behavior at the expense of the lender and show, as a result, a better credit performance. If the *monitoring* hypothesis holds, for the sub-group of collateralized loans one would not expect a difference in credit performance for similar borrowers on the basis of whether their loans are securitized or not. Also within the uncollateralized sub-group, borrowers of securitized loans would tend to perform poorly compared to the borrowers of non-securitized loans. This is because the bank, having sold the loan, is less likely to devote many resources to monitor borrower intensively.

Another possible explanation for the relative bad credit performance of securitized loans may be that banks are able to exploit their information advantage. Banks may securitize apparently better loans based on publicly observable characteristics, in order to signal quality while still exploiting their information advantage over outsiders. In fact, the *signaling* argument relies on the fact that outsiders could only roughly assess the credit quality of the borrower through observable indicators such as credit ratings or accounting statements. In contrast banks may possess a more accurate view on the future performance on the loans they originated due to their access to proprietary information on the borrower. According to this explanation, banks would have an incentive to securitize apparently good loans as they expect those loans to perform worse than what can be inferred by other investors based on observable characteristics. For example, there is evidence from trading in mortgage-backed securities suggesting that banks exploit their access to inside information (Drucker and Mayer, 2008) and that, prior to securitization, mortgage lenders adversely selected mortgages with higher prepayment risk (Agarwal et al., 2012).

This could be termed as the *lemons* hypothesis where over time borrowers of securitized loans perform worse than borrowers of non-securitized loans due to banks' ability of exploiting their information advantage over outside investors. In our setup, an inferior performance of companies of securitized loans compared to companies of non-securitized loans for both collateralized and uncollateralized instruments would be consistent with the *lemons* hypothesis, although it is difficult to rule out other possibilities that are not captured in our analysis. This is a limitation of our research.

3 Data and Methodology

3.1 Data

Data on individual loan deals is obtained from Dealogic-Loanware. It includes 4,652 euro-denominated syndicated loans, of which 1,795 are subsequently securitized. These loans are all granted between 2005 and 2007 by banks headquartered in the euro area.

Data on securitization activity comes from Dealogic-Bondware and Standard & Poor's.[3] We limit our sample to funded and cash-flow (balance-sheet) CLOs issued by euro-area banks.[4] We also exclude refinancing and loans granted to finance M&A activities. We add two additional fields to our dataset, which allow us to identify those loans that were eventually securitized. We do this by collecting loan-by-loan confidential information from all major European Trustees for loans issued between 2005 and 2007.[5] We further restrict our dataset to euro-denominated loans granted to borrowers whose headquarters are in the euro area. We exclude bank, other financial companies and utility firms from our sample. We further limit our sample and include only those borrowers for which Moody's calculates expected probabilities of default (i.e., *EDF*). We then carefully match our database on syndicated loans with information on *EDF* of each borrower underlying each loan from 2006 to 2010.[6] Overall, our final sample includes securitized loans to 89 borrowers matched with a broader sample of 429 borrowers of non-securitized loans.

The *EDF*, computed by Moody's KMV, is a forward-looking firm-specific measure of the actual probability of default calculated using a structural approach which builds on Merton's model to price corporate bond debt (Merton, 1974).[7] The final *EDF* value, expressed as a percentage, represents the implied risk of default and is constructed by combining companies' financial statements with stock market information and a proprietary default database maintained

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[3] An advantage of using Bondware and Standard & Poor's as the source for securitization data is that the names of the originator, date of issuance and deal proceeds are all registered.

[4] We exclude CLOs by non-bank institutions as our interest is on the effects of securitization on bank lending and monitoring.

[5] We only consider loans securitized from 2005 and 2007 as during the financial crisis the public CLO market ground to a halt. For the purposes of this work we do not consider the CLOs constructed to obtain central bank liquidity during the crisis.

[6] *EDF* values show the credit risk of the borrower and not the loan. We use the borrower's *EDF* —at the origination of the loan— to control for credit quality prior to securitization. Using borrower *EDF* is important in our setting because we want to capture the broad effect of reduced bank monitoring of securitization on firms.

[7] More specifically, the calculation of *EDF* builds on Vasicek and Kealhofer's extension of the Black-Scholes-Merton option-pricing.

by Moody's KMV. *EDF* developments are regularly used as a credit risk indicator by financial institutions, investors, central banks and regulators to monitor credit risks of borrowers.

Compared to other measures of expected bank risk, the KMV methodology has various advantages. First, it is not based on ratings which might be biased indicators of corporate risk due to conflicts of interest (Bolton, 2012). Second, unlike measures of default risks derived exclusively from accounting information—such as Z-scores—, *EDFs* are not a backward-looking indicator of risk.[8] Third, despite their simplifying assumptions *EDF* estimations of default risk show strong robustness to model misspecifications (Jessen and Lando, 2015).

During the recent financial crisis and compared to other measures of default risk, the *EDF* has done relatively well as a predictor of firms' risk from a cross-sectional perspective. That is, the relative positions of firms ranked according to their *EDF* levels in the year before the crisis were good predictors of rank ordering of default risk during the crisis (Munves et al., 2010). Analyzing the *EDF* performance in the crisis period both Korablev and Qu (2009) and Gokbayrak and Chua (2009) find that *EDF* predictive power of default risk is as good as or better than CDS spreads on their respective samples.

KMV best applies to publicly traded companies for which the value of equity is available and determined by the financial markets. By matching our syndicated loan database to those borrowers for which an *EDF* measure is available reduces our sample only to those borrowers that are listed on the stock market.[9] We use borrowers' *EDF* changes over time to measure the change in credit quality (Munves et al., 2000). An increase in a firm's *EDF* could well signal

[8] In unreported estimations we also use Z-score as an alternative credit risk measure using a larger sample of around 788 loans of which 151 are securitized. Similar to our setup with the EDF, we run regressions and undertake PSM analysis. Results obtained using Z-score, albeit it being a simplistic indicator of credit risk, broadly supports our main findings with EDF. These results are available upon request.

[9] In this paper we do not measure the ex-post performance of the loan but the borrower. Those observations where the borrower has defaulted after the loan issuance are included in our analysis until the period of default as we use the differences in *EDF* to measure the borrower performance.

greater default risk, even if the current absolute level might be excessive compared to a user's actual exposure. In this way *EDF* metrics can provide early warning of impending difficulties.[10]

3.2 Model and Variables

We first estimate a logistic model, to test *H1*, that links the probability of loan securitization to certain loan and borrower characteristics:

$$Pr(Securitized_i = 1|\mathrm{X}_i) = \Phi(\alpha EDF_i + L_i{}'\theta + Z_i{}'\gamma) \quad (1)$$

where *Pr* is the probability of securitization for loan *i* in the year following its issuance, Φ is the standard cumulative normal probability distribution, *EDF* captures the borrower's credit risk at the time of loan issuance, L is a set of variables controlling for loan characteristics, and Z is another set of variables controlling for other factors expected to impact of the probability of default. Loan characteristics include: *loan spread* (basis points), *loan size* (natural logarithm), *maturity* (years), presence of *subordination, collateral, instrument type, loan purpose* (corporate use, capital structure, project finance, transport finance and property finance). We also include a dummy variable, *sponsored*, which equals to 1 if the loan if the parent company of a subsidiary acts as a sponsor in the loan contract and 0 otherwise. We control for *industry* (construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport) and *date of issuance*. We take into account bank and syndicate characteristics as they might also impact on the probability of securitizing a loan (Sufi, 2007). We control for bank profitability, as less profitable banks are more likely to securitize loans (Casu et al., 2013). We control for *syndicate size* using the number of banks included on the syndicate. We also control for the ratio of *securitization active banks within the syndicate* over the total number of banks.

[10] It is worth to note here that Moody's KMV model does not adjust for the securitization status of the companies' loans.

Subsequently we estimate the following model (2) to examine the impact of securitization on borrower's future credit performance. Similar to previous studies (Benmelech et al., 2012; Wang and Xia, 2015) we utilize change in risk as the dependent variable in this setting.

$$\Delta EDF_i = f(\alpha Securitized_i + \delta EDF_i + L_i'\theta + Z_i'\gamma) \tag{2}$$

where *Securitized* is equal to 1 if the loan is securitized and 0 otherwise. *EDF* is utilized to control for borrower credit risk at the time of loan issuance. We use the same set of loan (*L*) and other control variables (*Z*) described above.

We track changes in *EDF* (ΔEDF) to proxy for the deterioration or improvement in borrowers' credit quality (henceforth performance) over time. Using this variable we examine the ex-post (i.e., after the loan has been securitized) credit performance of the borrower controlling for observable characteristics at the time of origination. We use three alternative measures of ΔEDF:

1. ΔEDF_A accounts for the change in borrowers' credit risk for three time periods (one, two and three years) starting from the year in which the loan is issued. For example, to calculate a 2-year forward ΔEDF_A for a loan issued in 2005, we take the difference in *EDF* for that borrower by subtracting the average values of 2007 from 2005.
2. ΔEDF_B measures the differences in borrowers' *EDF* between the year in which the loan is issued and three different time periods (i.e., 2008, 2009 and 2010) selected to take place during the financial crisis. For example, assume that loan *A* is issued in 2005 and loan *B* is issued in 2006, to compute the average ΔEDF_B for year 2008 for loan *A*, we take the difference between the *EDF* in 2008 and 2005. For loan *B*, we take the difference in *EDF* between 2008 and 2006. This alternative measure allows

us to consider *EDF* changes from the time of securitization to different stages of the financial crisis.

3. ΔEDF_C measures the change in borrowers' credit risk during the financial crisis. To account for this, we incorporate the ΔEDF for each borrower calculated as changes in *EDF* from the start of the financial crisis (third quarter of 2007) to three separate periods of the financial crisis (i.e., 2008, 2009 and 2010). For example, to calculate the ΔEDF_C for 2008, we take the difference between the average *EDF* in 2008 and that of the third quarter of 2007. The idea is that many of the inherent risks in a securitization structure could be of systemic nature and as a result materialize only in the event of a (large) financial crisis.

3.3 Descriptive Statistics

Descriptive statistics are presented in Table 1. In Panel A we display the mean, median, standard deviation and mean comparison (t-tests) of loan and borrower characteristics. We find that securitized loans have higher spreads, tend to be smaller in size and have a longer maturity than non-securitized loans. The number of banks in the loan syndicate and the ratio of banks active in securitization (to total banks) in the syndicate are almost identical for both groups. *EDFs* of companies whose loans are non-securitized are usually higher than for companies whose loans are securitized.[11] In Panel B we display the summary statistics for the dummy variables. We find that a large share of securitized loans are secured using collateral and tend to be leveraged.

[11] Descriptive statistics show that securitized loans, whose borrowers have lower EDFs, have higher spreads. This may seem to imply that borrowers with lower EDFs are paying higher spreads for loans. However, the spread reported in the descriptive statistics also captures the other characteristics of the securitized loans which may reflect the more risky nature of these loans especially being leveraged or having longer maturity. In the estimations reported below, we control for all the loan characteristics to capture the effect of securitization on future credit performance.

4 Results

4.1 Whole sample

In Table 2 we present the results for the logistic model by employing the level of credit risk (i.e., *EDF*) at the time of the issuance. Controlling for a set of micro and macro variables,[12] we find that the *EDF* coefficient is negatively related to the probability of loan securitization. This suggests that loans of borrowers with relatively higher default risk are less likely to be securitized. This finding supports, albeit at only 10% significance level, *H1* and shows that banks signal quality by retaining assets of poorer credit risk, as observed at issuance, and tend to securitize assets of initially better credit quality (Greenbaum and Thakor, 1987; DeMarzo, 2005; Instefjord, 2005). Given the weak significance, at the very least our results show that, at issuance, credit quality of borrowers whose loans are securitized are not different from borrowers whose loans are not securitized.

Subsequently, we estimate model (2) to see whether future performance differs between companies whose loans are securitized versus companies with non-securitized loans. Results are presented in Table 3 for all variations of ΔEDF variable. For ΔEDF_A we report a positive and significant coefficient for *Securitized* only for 3 year, suggesting that companies with securitized loans performed worse in the long run. We do not observe differing performance for change within 1 and 2 year periods. For ΔEDF_B we report a positive and significant coefficient for years 2009 and 2010, showing that the aftermath impact of the financial crisis was greater for the companies whose loans were securitized. We are also interested in changes in borrowers' relative

[12] Note that summary statistics on some of these variables are not reported to keep the tables parsimonious. All these statistics are available upon request.

performance during the financial crisis, measured by ΔEDF_C, which is calculated as the changes in *EDF* from the start of the financial crisis (Q3:2007) to three separate periods that take place during the financial crisis. Results show that *Securitized* has a positive relationship with ΔEDF_C and has a statistically significant coefficient for the 2009 and 2010 periods. This suggests that loans of borrowers whose default risk would materialize in the event of a systemic crisis were more likely to be securitized.[13]

So far we show that borrowers of securitized loans performed poorly when compared to borrowers of non-securitized loans. There may be two ways to explain these findings. It could be that borrowers of securitized loans may be performing more poorly due to banks' weaker incentives to carefully monitor borrowers (i.e., *monitoring* hypothesis). We test the *monitoring* hypothesis (i.e., H2) by examining the performance of borrowers whose loans are more reliant on bank monitoring. We hypothesize that collateralized loans, where assets are pledged against the loan by the borrower, do not require as much monitoring as uncollateralized loans. This is because the borrower, having her assets at stake, would be more vigilant about taking on excessive risks. If the monitoring hypothesis holds, then, there should not be performance differences between borrowers of securitized loans in comparison to borrowers of non-securitized loans within the sub-group of uncollateralized loans. In addition within the uncollateralized loans sub-group, borrowers of securitized loans should perform more poorly than borrowers of non-securitized loans due to banks' lesser monitoring incentives.

[13] A limitation of our research is that the period of analysis corresponds to the period of 2007-2009 financial crises. During the crisis the change of EDFs might be caused by some other shocks, apart from banks reduced monitoring incentives due to securitization, which may lead to companies being affected differently based on their sector and location. Even though we try to control for various factors in our set-up, we acknowledge that this is a limitation of our work.

4.2 Collateralized versus uncollateralized loans

We repeat our analysis and distinguish between those corporate loans requiring and not requiring collateral. We present results for all three versions of ΔEDF in Table 4. For ΔEDF_A we find significant but negative coefficients for the collateralized loans group for 1 and 2 year. This shows that borrowers of collateralized loans performed better if their loans were securitized. Conversely, in the uncollateralized group, *Securitized* is positive and statistically significant for all time horizons. In other words, for uncollateralized loans borrowers performed poorly if their loans were securitized.

We do not find any significant coefficients for ΔEDF_B (for all time horizons) if the loans were collateralized. However, within the uncollateralized loans we find that *Securitized* has a positive sign and statistically significant for all time horizons. The results show that borrowers of securitized loans were more likely to show a deteriorating performance if their loans do not require collateral. Results for ΔEDF_C for uncollateralized loans show significant and positive coefficients for all years, whereas we do not report any significant coefficients for collateralized loans.[14]

Overall, these results provide evidence suggesting that borrowers' performance of securitized loans deteriorates more if loans are uncollateralized. Results are consistent across all time horizons and more significant in the long-term. It is worthwhile to also note that the size of the coefficients of *Securitized* increases over time in all models which shows that the impact is larger in the long-term. These findings are plausible as the performance difference becomes more

[14] In untabulated results, we also run estimations for the full sample, rather than separating the two groups as collateralized and uncollateralized loans, and use an interaction variable, securitized x collateralized, instead. We find that the interaction variable has a negative and statistically significant coefficient. Results are more robust for change in EDF_A indicator for all periods and only significant for change in EDF_B and change in EDF_C in the long term. Overall, we arrive to similar conclusions to our original analysis where we divide the sample. These results are available upon request.

prevalent in the long-term as the effects of banks' reduced monitoring of the borrower gradually start influencing corporates' performance. These findings provide evidence for the *monitoring* hypothesis. Banks, having sold the loan to third parties, are less interested in monitoring the borrower which in turn, affects borrowers' performance. This interpretation is driven by the fact that we observe more deterioration in credit quality of borrowers for uncollateralized loans that are securitized. We do not find any evidence for the *lemons* hypothesis.

5 Robustness checks

5.1 Propensity Score Matching

As an alternative strategy to assess the robustness of our results we use a propensity score matching (PSM). This technique allows us measure the impact of securitization on borrower credit risk using a comparable sample of loans.

The analysis of the effect of securitization on borrowers' credit quality might raise self-selection concerns with regard to the decision to securitize certain loans. If credit performance of borrowers of securitized loans versus borrowers of non-securitized loans would have differed systematically regardless of securitization, then comparing credit risk of these borrowers might yield biased estimates on the impact of securitization. Under this assumption, if borrowers of securitized loans are found to perform differently, on average, than borrowers of non-securitized loans, the difference may be due to the effect of self-selection rather than to securitization. Strictly speaking, to test our hypothesis, we would need to know what would have happened to the credit quality of the borrowers of securitized loans had their loans not been securitized. Because it is impossible to observe the same loan in both states of the world, we need to find an appropriate proxy for the counterfactual performance of securitized loans. Good candidates to proxy for this counterfactual are non-securitized loans from which we construct our control group. We construct this control group using a PSM approach (Rosenbaum and Rubin, 1983) which allows us reduce the matching problem to a single dimension via the propensity score.

We match our loan sample using propensity scores to compare securitized and non-securitized loans, which are ex-ante (i.e., prior to securitization) similar in terms of their key observable characteristics most related to the probability of securitization. Importantly our control group —constructed from the non-securitized loans— is selected among those loans whose credit risk trajectory prior to securitization lies as close as possible to that of similar securitized loans. If we assume that there are no significant differences in unobservables between the two matched groups of loans —or that unobservables do not play a significant role on the potential outcome— the observed differential in performance (ΔEDF) can be attributed to the effect of having received the treatment, which in our setting is the securitization of the loan.

Through matching we restrict our inference to the sample of securitized and matched non-securitized loans. The impact of the treatment (securitization) on loan i, δ_i, is the difference between potential outcomes (ΔEDF) with and without treatment:

$$\delta_i = \Delta EDF_{1,i} - \Delta EDF_{0,i} \tag{3}$$

The impact of securitization over the sample would be the average treatment effect on the treated (ATT), computed as follows:

$$ATT = E(\Delta EDF_1 - \Delta EDF_0 | T = 1) \tag{4}$$

As indicated, the treated group (securitized loans, denoted T_i = 1 for loan i) is matched with a control group (non-securitized loans, denoted T_i = 0 for loan i) on the basis of its propensity score which is a function of loan and borrower observable characteristics:

$$P(X_i) = Pr(T_i = 1|X_i), with\ (0 < P(X_i) < 1) \tag{5}$$

In our setting, the propensity score, $P(X_i)$ is initially estimated with a probit model where the binary dependent variable has a value of one for securitized loans, and zero otherwise. The regressors, X_i include various borrower, loan, lender characteristics and year of issuance. A key variable here is the borrower's *EDF* —at loan origination— which controls for credit quality. We also account for *borrower industry*.[15] Loan characteristics include *price* (spread basis points), *size* (natural logarithm), *maturity* (years), presence of *guarantees*, *collateral*, *instrument type* and *loan purpose* (corporate use, capital structure, project finance, transport finance and property finance). We use bank *profitability* (average ROA of the banks within the lending syndicate) and *syndicate size* (the number of banks on the syndicate) to control for lender characteristics.

There needs to be sufficient overlap in the propensity scores to match securitized and non-securitized loans. We impose a common support condition $[(0 < P(X_i) < 1)]$ that restricts inference to treated and non-treated units with comparable propensity scores. That is, non-treated units whose propensity scores are lower (or higher) than the defined minimum (maximum) are dropped. We exclude loans that have a 0 or 1 propensity scores to satisfy the overlap condition of the treatment and control samples. We employ nearest-neighbor matching where each securitized loan is matched with those non-securitized loans with the closest propensity scores (Dehejia and Wahba, 2002):

$$C(P_i) = \min_j \left| P_i - P_j \right| \tag{6}$$

where by $C(P_i)$ represents the control group of loans j matched to treated loans i (on the estimated propensity score). P_i is the estimated propensity score for the treated loans i and P_j is the estimated propensity score for the control loans j. We calculate our control group using

[15] Namely: Construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport.

matching with and without replacement.[16] This allows us to increase the quality of the matching and decrease bias (Dehejia and Wahba, 2002). Our main results are constructed using one to one (1:1) matching where each securitized loan is matched with a single non-securitized loan.[17]

Our supplementary PSM analysis has some advantages and limitations. On the one hand, it does not depend on the assumptions related to a specific functional form. It also has the advantage of restricting our inference to the sample of securitized and non-securitized loans that are actually comparable in terms of their observables. On the other hand, the PSM procedure relies on a selection based on observables so that any corrections on selection bias are also based on observable characteristics. While we control for a rich set of covariates including borrower, loan and lender characteristics, it cannot be completely ruled out that the existence of unobservable characteristics may have a lingering bias on the treatment effect. In particular, we cannot rule out the possibility of predetermined borrower-lender matching having an impact on our results given our setting (Wang and Xia, 2015). We explain this further in Section 5.3 below, where we use an instrumental variable approach to account for this possible bias on our results.

5.2 PSM Results

To verify the quality of matching graphically we first plot the distribution of the propensity scores for both groups (securitized or non-securitized loans), before and after matching, for the whole sample (Figure 1). In the unmatched sample, the propensity score distribution of the non-securitized loans is skewed to the left. In contrast, in the matched sample the distribution of the

[16] In the latter case a non-securitized loan can be used as a match more than once.

[17] We also calculate results for two (1:2) and four (1:4) matches. Increasing the number of matches might also increase bias —as the second and fourth closest matches are usually further away from the treated loan than the first match. At the same time the use of multiple matches can decrease variance as the matched sample becomes larger (Rubin and Thomas, 2000).

two groups is similar. This suggests that the use of propensity score matching is appropriate in our context.[18]

Table 5 presents the results for all ΔEDF measures. For ΔEDF_A we find that for loans of the securitized (treatment) group, the treatment has increased their future *EDF* for time horizons over 1 year and that the highest impact is seen in year 3. This shows that the credit quality of borrowers whose loans are securitized deteriorates significantly in comparison to the control group. The highest impact is observed after three years as suggested by the coefficients for the average treatment of the treated (*ATT*). We find that ΔEDF_B is only significant for the year 2009 when the treated is matched with four controls. ΔEDF_B was expected to capture the dramatic shift in borrowers' *EDF* values immediately after the start of the financial crisis in 2008. We only marginally observed that effect in 2009. Similar results are obtained for ΔEDF_C in Table 2. In line with the results presented above, securitized loans performed worse in the post-crisis period, although only the difference in *EDF* in 2009 is statistically significant.

In Table 6 we present the results for propensity score matched estimations for the two sub-groups, i.e., collateralized and uncollateralized loans. We find that none of the coefficients for the ΔEDF variables are significant for loans that are collateralized. For the uncollateralized sample, coefficients of *ATT* are statistically significant and positively related to the probability of securitization for ΔEDF_A variables for 2 and 3 year horizons. It is worthwhile to note that for ΔEDF_A, *ATT* increases over time where the largest difference is reported in year 3. We do not find significant differences between the two groups when we utilize ΔEDF_B and ΔEDF_C. Overall, our results with PSM confirms that there is a performance difference between the two groups;

[18] Ex-ante loan characteristics for the matched sample show that the loans are similar across observable characteristics after matching. This table is available upon request.

however, this is not apparent when we test the difference during and after the 2007-2009 financial crisis.

5.3 Controlling for predetermined borrower-lender matching

In this section we address a potential source of bias in our results that may be caused by predetermined borrower-lender matching. As some banks may be more active in the securitization market, it could be that those loans granted to borrowers by securitization active banks may be more likely to be securitized. Also securitization active banks may also be more likely to lower their screening standards (e.g., Keys et al., 2011; Purnanandam, 2011; Dell'Ariccia, 2012; Nadauld and Weisbach, 2012) and lax screening standards can generate an effect that is observationally indistinguishable from the effect of reduced ex-post monitoring (Wang and Xia, 2015). In short, there may be fundamental differences between borrowers of securitization active and non-active banks. If these differences influence borrowers' selection by banks that are active in securitization and the monitoring effect (i.e., ΔEDF) then the borrower-lender matching may be endogenous.

Following Wang and Xia (2015) and Ross (2010) we use an instrumental variable approach to account for this possible bias using the geographic location of the borrower as instrument. We use dummy variables to represent the countries (i.e., regions) in which the borrowers' headquarters are located. Similar to the US (Wang and Xia, 2015), the concentration of securitization active banks varies substantially geographically across different countries within Europe. As firms are more likely to borrow from banks closer to where they are located (Petersen and Rajan, 2002; Degryse and Ongena 2005; Bharath et al. 2011; Dass and Massa 2011), borrowers in countries with large securitization markets are more likely to borrow from securitization active banks. On the other hand, the location of the borrowers should not systematically influence their *EDF*s. Overall, we believe that the instruments that we choose influence borrower-lender matching without directly affecting the borrowers' ΔEDF (monitoring measure), other than its effect through securitization. It is worth to note here that it is a challenging task to find suitable instrumental variables in these setups. Hence, we followed the approach of Wang and Xia (2015) and select regional dummy variables as instruments. In the US these variables may be more homogeneous in reflecting regional (or States') risk. However, in the European context EDF measures may vary across countries due to country level risk because the integration of economies and financial markets in Europe is more recent.[19]

We use seven country dummy variables for Germany, France, Spain, Italy, Netherlands, Ireland and Sweden.[20] These countries cover 91 percent of observations in our sample. We utilize a 2SLS estimator to implement the instrumental variable estimation. In the first stage, we regress the *Securitized* dummy variable on the seven country dummy variables and control for loan, syndicate and bank characteristics as well as for loan purpose, business industry and year. In a second stage we use the instrumented *Securitized* variable to run our main models.

Results are presented in Table 7 Panel A for the uncollateralized sample from which we drive our conclusions on the effect of securitization on monitoring incentives. In all models we still find positive and highly significant coefficients for *Securitized*. Our main finding, i.e., borrowers of securitized uncollateralized loans perform worse over time, remains after controlling for the possible selection bias that may be caused by predetermined borrower-lender

[19] To check whether EDF measures vary across countries in Europe due to country level risk, we ran an analysis by regressing EDF on country dummy variables. Results of this regression show that none of the country coefficients are statistically significant at 10% level. Furthermore, R^2 is very low at 0.05 which shows that countries do not have a significant explanatory power on EDF. These results are unreported and available upon request.

[20] The base group, which aggregately represents 9% of the loans in our sample, consists, of Belgium, Denmark, Finland, Greece, Hungary, Portugal and the United Kingdom.

matching. Larger performance differences are observed in the long-term which seems in line with theory as the impact of reduced lender monitoring would affect the borrower behavior more as time goes by.

Similar to Wang and Xia (2015) we find that the instrumental variable estimates (2nd stage) are larger in magnitude than our original results reported in Table 4. This means that the increase in the risk of borrowers, whose loans are uncollateralized, endogenously matched with their securitization-active banks takes place largely prior to origination (Wang and Xia, 2015). We use Sargan-Hansen and Basmann test of overidentifying restrictions to test the validity of our instruments. Results (reported in Table 7 Panel B) show that our instruments are not weak for the models capturing the long-term effects (year 2 and 3 for EDF_A, 2009 and 2010 for EDF_B *and* EDF_C).

6 Conclusions

We examine the relative performance of corporate borrowers whose loans were securitized in Europe during the period preceding the financial crisis. We find that banks did not select and securitize loans of lower quality borrowers to outsiders, providing evidence consistent with the *signaling* argument. Banks kept poorer quality corporate loans to signal the quality of the securitized assets to the investors. We also show that following securitization, the credit quality of borrowers whose loans are securitized deteriorated significantly over time compared to the control group. We find that poor performance is linked to the weakening in monitoring activities by banks after securitization as, within borrowers of securitized loans, uncollateralized ones show worse performance than collateralized ones.

In the post-crisis period, European policy makers, recognizing the potential benefits of securitization to the financial system, are considering policy options to transform and revive securitization markets in the EU (European Central Bank, 2014). Having a better understanding of the financial stability implications of securitization can help to develop a robust securitization market. Our results suggest that securitization might impact negatively on the credit quality of securitized loans over time. They also vouch for the advantages of setting up mechanisms to improve the information quality on the collateral pledged by borrowers. These might include credit registers with enhanced mark to market information on collateral values.

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Table 1

Descriptive Statistics

This table reports the summary statistics. Panel A reports the main loan and borrower characteristics for non-securitized and securitized loans separately. Spread is measured as basis points over LIBOR. Size of the loan is in million Euros. Maturity is in years. Syndicate size is the number of banks extending the loan jointly in the syndication. Securitization active banks is the number of banks in the syndication that are active in the securitization market divided by the total number of banks in the syndication. *EDF* is the expected default frequency, computed by Moody's KMV, of the borrower. Panel B reports other loan characteristics. Secured loans are collateralized. Subordinated shows the presence of subordination. Sponsored loans are the ones that are sponsored by the parent company. Instrument type includes Term loan, Term loan A, B, C and Credit facility. Rated loans are assigned a credit rating by at least one credit rating agency. Leveraged shows if the loan is leveraged. Investment grade shows if the loan has an investment grade credit rating. Highly leveraged shows if the loan is highly leveraged.

Panel A

	Non-securitized (N=429)			Securitized (N=89)			Mean comparison
Loan characteristics	Mean	Median	Std. dev	Mean	Median	Std. dev	t-values
Spread	138	87.5	160	310	275	181	-9.01***
Size	670	242	1,328	435	170	819	1.60
Maturity	5.8	5.6	2.1	8.1	8	1.4	-9.88***
Syndicate size	13.9	11	10.1	13.4	10	11.4	0.41
Securitization active banks	0.69	0.69	0.18	0.69	0.64	0.19	-0.00
EDF of the borrower (%)	0.41	0.08	1.31	0.17	0.05	0.31	1.72*

Panel B - Percentage of loans

	Non-securitized	Securitized
Secured	35.79%	52.85%
Subordinated	4.22%	17.99%
Sponsored	53.47%	97.02%
Instrument type		
Term loan	29.01%	14.64%
Term loan A	9.82%	16.13%
Term loan B	5.82%	28.54%
Term loan C	4.19%	26.18%
Credit facility	12.82%	0.12%
Other	38.34%	14.39%
Risk and credit ratings		
Leveraged	53.82%	98.88%
Investment grade	45.51%	1.12%
Highly leveraged	0.67%	0.00%
Rated	12.79%	6.45%

Table 2
Probability of a loan being securitized

This table presents coefficient estimates for logit regression estimating the probability of loan securitization within one year of loan issuance. *EDF* is the expected default frequency, computed by Moody's KMV, at the time of loan issuance. We control for observable loan and syndicate characteristics at the time of loan origination. Loan characteristics include: spread (basis point over LIBOR), size, maturity, if the loan is secured, if the loan is subordinated, if the loan is sponsored, loan rating, type of loan and if the loan is leveraged. Syndicated characteristics include the number of the banks in the lending syndicate and the ratio of securitization active banks within the syndicate over the total number of banks. Bank characteristics include average profitability of the banks within the syndicate and controls for possible lead bank effects on the syndicate. Loan purpose is controlled for using dummy variables (categorized as corporate use, capital structure, project finance, transport finance and property finance). Business Industry is controlled for using dummy variables (categorized as construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport). Year dummy variables control for the macroeconomic conditions. Robust standard errors are reported in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

EDF	-0.690*
	(0.392)
Loan spread	0.002
	(0.208)
Loan size	0.001**
	(0.025)
Maturity	0.316***
	(0.000)
Secured	0.033
	(0.924)
Subordinated	0.252
	(0.829)
Sponsored	0.433
	(0.617)
Rated	-0.366
	(0.64)
Leveraged	2.249**
	(0.028)
Term loan	1.242***
	(0.299)
Term loan A	2.174***
	(0.313)
Term loan B	3.171***
	(0.318)
Term loan C	3.061***
	(0.387)
Credit facility	0.289
	(0.336)
Syndicate's average bank profitability	-0.517
	(0.160)
Syndicate size	0.068***
	(0.008)
Securitization active banks in the syndicate	1.844**
	(0.024)
2006	0.907***
	(0.001)
2007	1.058***
	(0.002)
Controls for:	
Loan purpose	Yes
Business industry	Yes
Number of observations	518
R-squared	0.5

Table 3

Change in default risk of companies by loans securitization

This table presents coefficient estimates for OLS regressions estimating the change in EDF. EDF is the expected default frequency, computed by Moody's KMV, at the time of the loan issuance. Δ in EDF proxies for the deterioration or improvement of the borrower credit quality over time to measure the ex-post performance of the borrower of the loan. For example if the loan is issued in 2005 then Δ in EDF within 1 year of the borrower equals the EDF in 2006 minus the EDF in 2005 divided by EDF in 2005. Δ in EDF proxies for the deterioration or improvement of the borrower credit quality over time to measure the ex-post performance of the borrower of the loan. For example if the loan is issued in 2006 then Δ in EDF from the loan issuence to 2008 equals the EDF in 2008 minus the EDF in 2006 divided by EDF in 2006. Δ in EDF from Q3:2007 proxies for the deterioration or improvement of the borrower credit quality from the start of the financial crisis to following three years to measure ex-post performrance. We control for observable loan and syndicate characteristics at the time of loan origination. Loan characteristics include: spread (basis point over LIBOR), size, maturity, if the loan is secured, if the loan is subordinated, if the loan is sponsored, if the loan is rated, type of loan and if the loan is leveraged. Syndicated characteristics include the number of the banks in the lending syndicate and the ratio of securitization active banks within the syndicate over the total number of banks. Loan purpose is controlled for using dummy variables categorised as corporate use, capital structure, project finance, transport finance and property finance. Business Industry is controlled for using dummy variables categorised as contraction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport. Year dummy variables control for the macroeconomic conditions. Robust standard errors are reported in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Δ in EDFA within			*Δ in EDF_B from issuence to*			*Δ in EDF_C from Q3:2007 to*		
	1 year	2 year	3 year	2008	2009	2010	2008	2009	2010
Securitized	0.074	0.349	1.762***	0.461	1.599**	2.104**	0.431	1.643**	2.152**
	(0.110)	(0.322)	(0.604)	(0.303)	(0.750)	(0.845)	(0.263)	(0.743)	(0.847)
EDF	0.146***	0.584***	0.696***	0.212***	1.486***	1.602***	0.474***	1.727***	1.847***
	(0.026)	(0.075)	(0.137)	(0.069)	(0.164)	(0.188)	(0.060)	(0.163)	(0.188)
Loan spread	-0.001	-0.001	-0.001	-0.001	-0.000	0.001	-0.001	0.001	0.002
	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	(0.004)	(0.001)	(0.003)	(0.004)
Loan size	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity	-0.037*	-0.079	-0.152	-0.113**	-0.160	-0.103	-0.081*	-0.129	-0.072
	(0.021)	(0.061)	(0.111)	(0.056)	(0.138)	(0.158)	(0.048)	(0.137)	(0.159)
Secured	0.092	-0.317	-1.010**	-0.311	-0.665	-0.628	-0.195	-0.487	-0.478
	(0.090)	(0.254)	(0.465)	(0.235)	(0.584)	(0.658)	(0.204)	(0.578)	(0.660)
Subordinated	0.422	0.815	0.934	0.542	0.819	0.085	0.138	0.457	-0.275
	(0.303)	(0.886)	(1.612)	(0.817)	(2.006)	(2.288)	(0.709)	(1.986)	(2.295)
Sponsored	-0.332**	-1.298***	-3.321***	-0.906**	-1.966**	-3.869***	-0.723**	-1.850**	-3.725***
	(0.135)	(0.385)	(0.732)	(0.359)	(0.924)	(0.997)	(0.312)	(0.917)	(1.003)
Rated	0.106	-0.158	-0.541	0.179	-0.306	-0.955	0.129	-0.369	-1.016
	(0.091)	(0.262)	(0.476)	(0.241)	(0.565)	(0.650)	(0.209)	(0.560)	(0.653)
Leveraged	0.202	1.455***	3.425***	0.625*	2.471***	3.333***	0.461	2.245***	3.114***
	(0.129)	(0.365)	(0.674)	(0.335)	(0.803)	(0.913)	(0.291)	(0.796)	(0.916)
Credit facility	0.031	0.435	1.084	0.184	0.765	1.278	0.196	0.772	1.282
	(0.145)	(0.412)	(0.771)	(0.384)	(0.916)	(1.047)	(0.333)	(0.907)	(1.050)
Term loan	-0.123	-0.145	-0.306	-0.007	-0.299	-0.041	-0.150	-0.410	-0.507
	(0.137)	(0.370)	(0.435)	(0.362)	(0.787)	(0.355)	(0.317)	(0.827)	(0.718)
Term loan A	0.507	0.286	0.870	0.104	0.809	0.450	0.866	0.286	0.998
	(0.718)	(0.918)	(1.086)	(0.365)	(1.633)	(1.809)	(1.079)	(0.918)	(1.066)
Term loan B	0.066	0.075	-0.243	0.055	-0.043	-0.224	0.040	-0.119	-0.285
	(0.144)	(0.419)	(0.777)	(0.393)	(0.967)	(1.093)	(0.341)	(0.957)	(1.096)
Term loan C	0.087	0.113	-0.358	0.006	0.006	-0.413	-0.071	-0.136	-0.543
	(0.159)	(0.456)	(0.851)	(0.430)	(1.068)	(1.205)	(0.374)	(1.057)	(1.209)
Syndicate's average bank profitability	-0.119	-0.130	0.552	0.114	0.257	0.668	0.138	0.361	0.760
	(0.076)	(0.220)	(0.405)	(0.205)	(0.494)	(0.561)	(0.178)	(0.489)	(0.563)
Syndicate size	-0.001	-0.002	-0.041*	-0.011	-0.030	-0.042	-0.010	-0.031	-0.043
	(0.004)	(0.012)	(0.022)	(0.011)	(0.027)	(0.030)	(0.010)	(0.026)	(0.031)
Securitization active banks in syndicate	-0.483**	-1.769***	-4.405***	-2.209***	-2.572*	-2.849*	-1.842***	-2.390*	-2.636*
	(0.201)	(0.599)	(1.099)	(0.559)	(1.314)	(1.478)	(0.486)	(1.309)	(1.491)
2006	0.207***	0.838***	1.262***	-0.058	-0.360	0.501	-0.258	-0.504	0.360
	(0.073)	(0.209)	(0.382)	(0.194)	(0.482)	(0.536)	(0.168)	(0.481)	(0.542)
2007	1.281***	4.141***	3.782***	0.577*	1.319	1.874**	0.165	0.960	1.506
	(0.134)	(0.379)	(0.687)	(0.348)	(0.829)	(0.942)	(0.302)	(0.820)	(0.944)
Controls for:									
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	474	460	446	446	417	428	444	412	423
R-squared	0.26	0.36	0.24	0.06	0.21	0.24	0.16	0.26	0.27

Table 4

Change in default risk of companies by loan securitization: collateralized versus uncollateralized loans

This table presents coefficient estimates for OLS regressions estimating the change in *EDF*. *EDF* is the expected default frequency, computed by Moody's KMV, at the time of the loan issuance. ΔEDF_A are changes in borrower credit quality to a certain period after issuance. ΔEDF_B are changes in borrower credit quality from issuance to different periods of the financial crisis. ΔEDF_C are changes in borrower credit quality during the financial crisis. *Securitized* equals to 1 if the loan is securitized and 0 otherwise. We control for observable loan and syndicate characteristics at the time of the loan origination. Loan characteristics include: spread (basis point over LIBOR), size, maturity, if the loan is secured, if the loan is subordinated, if the loan is sponsored, if the loan is rated, type of loan and if the loan is leveraged. Syndicated characteristics include the number of the banks in the lending syndicate and the ratio of securitization active banks within the syndicate over the total number of banks. Bank characteristics include average profitability of the banks within the syndicate and controls for possible lead bank effects on the syndicate. Loan purpose is controlled for using dummy variables (categorized as corporate use, capital structure, project finance, transport finance and property finance). Business Industry is controlled for using dummy variables (categorized as construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport). Year dummy variables control for the macroeconomic conditions. Robust standard errors are reported in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Collateralized loans								
	Δ in EDFA within			*Δ in EDF_B from issuance to*			*Δ in EDFC from Q3:2007 to*		
	1 year	2 year	3 year	2008	2009	2010	2008	2009	2010
Securitized	-0.476**	-1.613**	-0.714	-0.595*	-0.256	-0.914	-0.032	0.406	1.541
	(0.209)	(0.764)	(0.840)	(0.350)	(0.802)	(1.122)	(0.184)	(0.731)	(1.161)
EDF	0.138***	0.584***	0.612***	0.080***	1.405***	1.672***	0.474***	1.805	2.072***
	(0.040)	(0.040)	(0.140)	(0.058)	(0.126)	(0.182)	(0.031)	(0.114)	(0.187)
Controls for:									
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Syndicate characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	143	129	124	124	113	118	124	113	118
R-squared	0.36	0.38	0.44	0.27	0.67	0.62	0.76	0.78	0.65

	Uncollateralized loans								
	Δ in EDFA within			*Δ in EDF_B from issuance to*			*Δ in EDF_C from Q3:2007 to*		
	1 year	2 year	3 year	2008	2009	2010	2008	2009	2010
Securitized	0.467***	1.657***	3.767***	0.866**	2.873***	3.508***	0.568	2.739***	3.413***
	(0.131)	(0.324)	(0.329)	(0.438)	(1.093)	(1.156)	(0.408)	(1.098)	(1.148)
EDF	0.143***	0.525***	1.305***	0.685***	2.061***	2.181***	0.509***	1.718***	1.883***
	(0.051)	(0.129)	(0.329)	(0.172)	(0.438)	(0.462)	(0.161)	(0.443)	(0.462)
Controls for:									
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Syndicate characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	331	331	322	322	304	310	320	299	305
R-squared	0.23	0.39	0.67	0.07	0.09	0.15	0.05	0.07	0.14

Table 5

Change in default risk of companies by loans securitization using propensity score matching

The table reports the average treatment effect on the treated (*ATT*). It shows propensity score matching estimates of the average treatment effect of securitization on default risk, ΔEDF, of the securitized loans. The average treatment effect of securitization on ΔEDF is estimated as the difference between securitized loans' mean ΔEDF and that of matched non-securitized loans. ΔEDF_A proxies for the deterioration or improvement of the borrower credit quality over time to assess the ex-post performance of the borrower of the loan. For example if the loan is issued in 2005 then ΔEDF within 1 year of the borrower equals the *EDF* in 2006 minus the *EDF* in 2005 divided by *EDF* in 2005. ΔEDF_C proxies for the deterioration or improvement of the borrower credit quality from the start of the financial crisis (Q3:2007) to three different periods of the financial crisis. The objective is to measure relative changes in default risk during the crisis. Robust standard errors are bootstrapped and presented in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Number of matched controls			
	One	Two	Four	Number of observations
ΔEDF_A within				
1 year	0.077	0.130	0.132	474
	(0.076)	(0.099)	(0.080)	
2 year	0.814*	0.801**	0.847**	460
	(0.426)	(0.393)	(0.365)	
3 year	1.867**	2.076**	2.010**	446
	(0.947)	(0.818)	(0.843)	
ΔEDF_B from issuance to				
2008	0.172	0.194	0.372	446
	(0.438)	(0.346)	(0.325)	
2009	2.136*	2.118**	1.864*	417
	(1.282)	(1.011)	(0.986)	
2010	1.917	1.492	1.663	428
	(1.714)	(1.643)	(1.476)	
ΔEDF_C from Q3:2007 to				
2008	0.213	0.241	0.332	444
	(0.458)	(0.328)	(0.276)	
2009	2.050**	2.177**	1.879*	412
	(0.976)	(0.969)	(1.027)	
2010	1.666	1.554	1.622	423
	(1.706)	(1.672)	(1.826)	

Table 6

Change in default risk of companies by loan securitization: collateralized versus uncollateralized loans using propensity score matching

The table reports the average treatment effect on the treated (*ATT*). It shows propensity score matching estimates of the average treatment effect of securitization on the default risk, ΔEDF, of the securitized loans. The average treatment effect of securitization on a ΔEDF is estimated as the difference between securitized loans' mean ΔEDF and that of matched non-securitized loans. ΔEDF_A are changes in borrower credit quality to a certain period after issuance. For example if the loan is issued in 2005 then ΔEDF within 1 year equals the *EDF* in 2006 minus the *EDF* in 2005 divided by *EDF* in 2005. ΔEDF_B are changes in borrower credit quality from issuance to different periods of the financial crisis. For example if the loan is issued in 2006 then ΔEDF from the loan issuance to 2008 equals the *EDF* in 2008 minus the *EDF* in 2006 divided by *EDF* in 2006. ΔEDF_C are changes in borrower credit quality during the financial crisis. Robust standard errors are bootstrapped and presented in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Collateralized loans		Uncollateralized loans	
	ATT	Number of observations	*ATT*	Number of observations
ΔEDF_A within				
1 year	0.047	143	0.373	331
	(0.111)		(0.274)	
2 year	0.195	129	1.773***	331
	(0.493)		(0.689)	
3 year	1.022	124	3.906**	322
	(1.567)		(1.919)	
ΔEDF_B from issuance to				
2008	0.198	124	0.411	322
	(0.388)		(0.961)	
2009	0.574	113	2.004	304
	(1.951)		(2.849)	
2010	2.165	118	1.531	310
	(3.481)		(2.702)	
ΔEDF_C from Q3:2007 to				
2008	0.193	124	0.131	320
	(0.276)		(0.727)	
2009	0.555	113	2.082	299
	(2.233)		(2.927)	
2010	2.141	118	1.697	305
	(2.128)		(2.753)	

Table 7

Instrumental variable regressions to control for predetermined borrower-lender matching in uncollateralized loans

This table presents coefficient estimates for 2SLS regressions estimating the change in *EDF*. *EDF* is the expected default frequency, computed by Moody's KMV, at the time of the loan issuance. ΔEDF_A are changes in borrower credit quality to a certain period after issuance. ΔEDF_B are changes in borrower credit quality from issuance to different periods of the financial crisis. ΔEDF_C are changes in borrower credit quality during the financial crisis. *Securitized* equals to 1 if the loan is securitized and 0 otherwise. We control for observable loan and syndicate characteristics at the time of the loan origination. Loan characteristics include: spread (basis point over LIBOR), size, maturity, if the loan is secured, if the loan is subordinated, if the loan is sponsored, if the loan is rated, type of loan and if the loan is leveraged. Syndicated characteristics include the number of the banks in the lending syndicate and the ratio of securitization active banks within the syndicate over the total number of banks. Bank characteristics include average profitability of the banks within the syndicate and controls for possible lead bank effects on the syndicate. Loan purpose is controlled for using dummy variables (categorized as corporate use, capital structure, project finance, transport finance and property finance). Business Industry is controlled for using dummy variables (categorized as construction and property, high-tech industry, infrastructure, population related services, state, manufacturing and transport). Year dummy variables control for the macroeconomic conditions. In the selection equation country dummy variables - Germany, Ireland, Italy, Netherlands, Spain, Sweden and France- equals to 1 if the borrower is from one of these countries and 0 otherwise. The base group consists of Belgium, Denmark, Finland, Greece, Hungary, Portugal and the United Kingdom. Robust standard errors are reported in parenthesis. ***, ** and * represents significance levels at 1%, 5% and 10%, respectively.

	Δ *in* EDF_A *within*			Δ *in* EDF_B *from issuance to*			Δ *in* EDF_C *from Q3:2007 to*		
	1 year	2 year	3 year	2008	2009	2010	2008	2009	2010
Panel A: Second stage									
Securitized (Instrumented)	2.064***	8.880***	14.933***	4.948**	15.435***	18.953***	4.501**	15.438***	19.131***
	(0.649)	(2.134)	(4.381)	(2.072)	(5.745)	(6.437)	(1.952)	(5.812)	(6.492)
EDF	0.177***	0.695***	1.579***	0.787***	2.045***	2.108***	0.609***	1.706***	1.812***
	(0.062)	(0.208)	(0.415)	(0.195)	(0.512)	(0.568)	(0.184)	(0.520)	(0.575)
Controls for:									
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Syndicate characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	331	331	322	322	304	310	320	299	305
Panel B: First stage									
Germany	-0.051	-0.035	-0.055	-0.051	-0.035	-0.031	-0.025	-0.028	-0.054
	(0.063)	(0.060)	(0.061)	(0.061)	(0.060)	(0.059)	(0.060)	(0.059)	(0.063)
Ireland	-0.307**	-0.313**	-0.320**	-0.307**	-0.313**	-0.309**	-0.282*	-0.277*	-0.320***
	(0.144)	(0.144)	(0.142)	(0.143)	(0.143)	(0.143)	(0.144)	(0.141)	(0.144)
Italy	0.002	0.013	-0.001	0.001	0.012	0.017	0.014	0.013	-0.000
	(0.077)	(0.074)	(0.074)	(0.074)	(0.074)	(0.073)	(0.073)	(0.070)	(0.077)
Netherlands	-0.027	0.007	-0.006	-0.027	0.007	0.020	0.014	0.011	-0.005
	(0.086)	(0.074)	(0.074)	(0.083)	(0.074)	(0.076)	(0.074)	(0.072)	(0.076)
Spain	0.067	0.084	0.063	0.067	0.085	0.090	0.096	0.089	0.063
	(0.065)	(0.062)	(0.063)	(0.063)	(0.062)	(0.062)	(0.062)	(0.060)	(0.065)
Sweden	-0.014	-0.017	-0.016	-0.014	-0.017	-0.011	-0.017	-0.016	-0.015
	(0.082)	(0.081)	(0.080)	(0.080)	(0.081)	(0.080)	(0.079)	(0.078)	(0.082)
France	-0.049	-0.063	-0.047	-0.050	-0.063	-0.059	-0.079	-0.082	-0.046
	(0.065)	(0.061)	(0.062)	(0.062)	(0.060)	(0.059)	(0.060)	(0.059)	(0.065)
2^{nd} stage control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.31	0.32	0.35	0.35	0.36	0.38	0.35	0.36	0.38
Overidentifiying tests									
Pr (Sargan-Hansen)	0.062	0.299	0.193	0.003	0.157	0.313	0.007	0.154	0.478
Pr (Basmann)	0.076	0.340	0.227	0.004	0.189	0.358	0.009	0.185	0.527

Figure 1

Distribution of propensity score of securitized and non-securitized loans before and after matching

This figure displays the distribution of the propensity scores for securitized and unsecuritized loans before and after propensity score matching for the whole sample to verify the quality of matching graphically. In the unmatched sample (left panel), the propensity score distribution of the non-securitized loans is skewed to the left. In contrast, in the matched sample the distribution of the two groups is similar.