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by Ugo Albertazzi, Margherita Bottero, Leonardo Gambacorta and Steven Ongena

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Asymmetric information and the securitization of SME loans*

Ugo Albertazzi
(Bank of Italy)

Margherita Bottero
(Bank of Italy)

Leonardo Gambacorta
(Bank for International Settlements and CEPR)

Steven Ongena
(University of Zurich, Swiss Finance Institute, KU Leuven and CEPR)

Abstract

Using credit register data for loans to Italian firms we test for the presence of asymmetric information in the securitization market by looking at the correlation between the securitization (risk-transfer) and the default (accident) probability. We can disentangle the adverse selection from the moral hazard component for the many firms with multiple bank relationships. We find that adverse selection is widespread but that moral hazard is confined to weak relationships, indicating that a strong relationship is a credible enough commitment to monitor after securitization. Importantly, the selection of which loans to securitize based on observables is such that it largely offsets the (negative) effects of asymmetric information, rendering the overall unconditional quality of securitized loans significantly better than that of non-securitized ones. Thus, despite the presence of asymmetric information, our results do not accord with the view that credit-risk transfer leads to lax credit standards.

JEL classification: D82, G21.
Keywords: securitization, SME loans, moral hazard, adverse selection.

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1. Introduction

A well-functioning securitization market eases the flow of credit to the real economy by helping banks to distribute their risk, diversify their funding, and expand their loans. A deep market for asset-backed securities (ABS) is especially valuable during financial crises, often accompanied by slow-downs in the supply of bank credit, and for supporting financing to small and medium-sized enterprises (SMEs), the least able to tap into alternative sources of financing. In line with these considerations, a number of initiatives have been promoted in the euro area to restart the local ABS market, which has never fully recovered from the massive disruption observed after the collapse of Lehman.[1]

The difficulties in reactivating the securitization market could be related to the inherent limitation of this financial intermediation model. The so-called originate-to-distribute model has been blamed for igniting financial excesses and causing the financial crisis, due to the presence of asymmetric information. In particular, as banks heavily rely on the use of non-verifiable *soft information* about borrowers, the possibility to off-load credit risk via securitization may undermine banks' incentives to screen borrowers at origination or to keep monitoring them once the loan is sold, giving rise to adverse selection and moral hazard (see Gorton and Pennacchi, 1995; Morrison, 2005; Parlour and Plantin, 2008).[2]

Despite a burgeoning literature on this topic, the extent to which securitizations are fundamentally flawed by asymmetric information is still undetermined. Theoretically, it has

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[1] The euro area ABS market withered after the Lehman crisis. The measures taken by both the European Central Bank (ECB) and other policymakers aimed to assist the gradual recovery of the economy from the sovereign debt crisis. In 2014 the ECB launched the asset-backed securities purchase programme (ABSPP). See https://www.ecb.europa.eu/press/pr/date/2014/html/pr141002_1.en.html) and BCBS and IOSCO (2015) for a discussion. Originators continue to retain newly issued deals in order to create liquidity buffers and to use the assets as collateral with central banks (AFME, 2014).

[2] These asymmetric information frictions may further increase when the value of the collateral used to secure the underlying loan falls, as it is likely to do in crisis times (Chari et al., 2010).

been emphasised that banks may find ways to overcome frictions due to asymmetric information, via signalling or commitment devices, for instance by retention (Chemla and Hennessy, 2014). Empirical studies provide a mixed picture on the extent to which asymmetric information impairs the functioning of securitizations (among others, Keys et al., 2010, Albertazzi et al., 2015).

We contribute to this debate by assessing the role of asymmetric information in that segment of the securitization market where it is likely to be most pervasive, i.e., securities backed by loans to SMEs. This segment of the securitization market has not been empirically investigated, despite its prominence in the current policy debate. Our interest is also related to the greater opacity surrounding SME loans, in the comparison to, for example, housing loans or syndicated loans to (large) firms.

A second crucial feature of our paper is related to the very detailed loan-level dataset used, which includes information on the performance of *both* securitised and non-securitised loans originated by all banks in the sample. For all these exposures we observe the performance in terms of default status, even for loans that end up being securitised at some point in their life. In particular, we rely on very granular, monthly information taken from Bank of Italy Credit Register and Supervisory Records on the entire population of firms borrowing from Italian banks over the years 2002–2007, which we enhance by tracking the status of loans (securitized and not securitized) until 2011.

In terms of methodology, we build on the framework originated by Chiappori and Salanié (2000) in their seminal paper testing asymmetric information in insurance contracts. This methodology was first applied in the context of the securitization market by Albertazzi et al. (2015), who study mortgage loans. This methodology consists in jointly estimating a model for the probability of a loan being involved in a securitization deal and one for the probability that it deteriorates. We surmise that a securitization is affected by asymmetric information if – conditional on the characteristics of the securitized loans which are observable to the investors – there is a positive correlation between the errors of the model for the probability of a loan being securitized, and those for the probability that the loan goes into default (or deteriorates).

A salient contribution of our analysis is, however, that we can explore what form the information asymmetries take, distinguishing between frictions due to adverse selection and those stemming from moral hazard. We rely on the premise that selecting versus monitoring of borrowers by a lender may affect the other financiers differently. Borrower selection will affect *all financiers* almost equally while borrower monitoring by its very nature will involve and affect mainly *the monitoring lender*.[3] This reasoning becomes relevant in our context due to the fact that borrowers maintain multiple bank relationships, of which only a few may involve securitized loans. Multiple bank relationships, then, can be used to separate moral hazard from adverse selection.

The main results can be summarized as follows. We document the presence of asymmetric information, mainly in the form of adverse selection. Moral hazard is limited to credit exposures characterized by weak firm-bank relationship ties, indicating that a tight credit relationship is a credible commitment to continue monitoring after securitization. Importantly, despite these findings, our evidence does not support the notion that securitization may lead to excessively lax credit standards. Indeed, the selection of securitized loans based on observables is such that it largely compensates for the effects of asymmetric information, rendering the unconditional quality of securitized loans significantly better than that of non-securitized ones. This is consistent with the notion that markets anticipate the presence of asymmetric information and

[3] We do not rule out that monitoring of one bank could have spillover effects on the risk borne by other financial intermediaries. As we will explain in detail below, our identification strategy holds under rather general assumptions on the presence of spillovers.

seek protection by requiring that the loans securitized are of sufficiently high observable quality.

The rest of the paper is organized as follows. Section 2 provides a brief overview of the literature. Section 3 describes the data. Section 4 illustrates the empirical strategy. Section 5 discusses the findings. Section 6 concludes.

2. Review of the relevant literature

Our results add to a large empirical literature that tries to assess the effects of asymmetric information problems in the originate-to-distribute (OTD) model (Purnanandam, 2011). As mentioned above, the issue is still largely unresolved, both on the theoretical and on the empirical side. On the theoretical side, Parlour and Plantin (2008) and Gorton and Pennacchi (1995) demonstrate that the possibility to securitize loans leads to a deterioration in the quality of the securitized loan, via adverse selection at the origination. Mishkin (2008) and Stiglitz (2010) reach the same conclusions but focus on the role played by moral hazard after securitization. At the same time, a more recent paper by Chemla and Hennessy (2014) illustrates how in such a setup a number of equilibria may arise, and that in some cases the distortions arising from informational asymmetries are endogenously resolved via signaling devices adopted by banks through the retention of part of the securitized loans.

On the empirical side, a number of studies document that the OTD model indeed leads to the securitization of loans of a quality lower than average. For ABS backed by mortgages, Keys et al. (2009, 2010) measure the default rate of a sample of sub-prime mortgage loans and find evidence of the presence of adverse selection. Purnanandam (2011) also finds that banks with high involvement in the securitization market during the pre-global-crisis period originated excessively poor-quality mortgages. This result, however, supports the view that the originating banks did not expend resources in screening their borrowers. Bord and Santos (2015) document similar findings for corporate ABS.

Different conclusions are reached by Albertazzi et al. (2015), who investigate banks' behaviour related to the larger part of the market for securitized assets, i.e., prime mortgages, and find that securitized loans are even less risky than non-securitized loans, at least in the first years of activity. Similar results are obtained by Benmelech et al. (2012) for collateralized loan obligations (CLOs), a form of securitization in which the underlying loans are to medium-sized and large businesses (typically a fraction of syndicated loans). They find that adverse selection problems in corporate loan securitization are less severe than commonly believed: these loans perform no worse and, by some criteria, even better than non-securitized loans of comparable credit quality. Since securitized loans are typically fractions of syndicated loans, the authors claim that the mechanism used to align incentives in a lending syndicate also reduces adverse selection in the choice of the CLO collateral.[4] Finally, a recent paper by Kara et al. (2015) looks at the interest rate on corporate ABS backed by syndicated loans and rejects the view that securitization lead to lower credit standards.

Our paper contributes to the literature in three ways. First, we look at ABS backed by loans to SMEs, which have been so far neglected in the literature due to data availability. This is an important extension as SMEs would be those firms most likely to benefit from an active securitization market, and have a key role in many advanced economies.[5] Second, our dataset allows us to track securitizations over time and exploit the multiple-lender feature of borrowers to isolate the relation between securitization and credit quality even after the loan disappears

[4] The difference between our results and those in Benmelech et al. (2012) are apparent. One way to reconcile the two works is by considering the fact that SMEs loans are more opaque than CLOs. Along similar lines, Sufi (2007) shows that the more opaque the borrower is, the more concentrated the syndicate will be.

[5] For example, in the euro area economy, they employ two thirds of the labor force and produce around 60 per cent of the value added from the business sector.

from the originating bank's balance sheet, and essentially until it is repaid or written off. Finally, we provide a novel approach to test for the presence of adverse selection and moral hazard.

3. Data description

Italy's asset securitization market developed much later than that of the U.S., originating with the introduction of a specific Securitization Law and the launch of the single European currency in 1999. However, euro-denominated securitization on performing loans in Italy started only in 2001 as in the first two years after the introduction of the law securitization activity was scarce, and mainly related to bad loans. Securitization activity flourished in the period 2001-2006 and then shrunk during turmoil in 2007, coming to a complete stop in 2008 after the collapse of Lehman Brothers. Securitization survived only in the form of retained securitization as a source of collateral for refinancing operations.[6]

This paper analyzes the whole population of loans originated by Italian banks active in the securitization market over the period 1997-2006.[7] In order to have the complete picture of borrowers' bank relationships, we integrate this data with information on all other loans extended to the firms already in the sample by other (non-securitizing) banks. We track all these lending exposures until the amount borrowed is repaid, written off or, in case they are still active, until the end of 2011.

Taking advantage of the data in the supervisory records, we gather detailed information on which of these exposures have been securitised, when, by how much and with which Special

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[6] See Financial Stability Report, Bank of Italy, 2/2011 https://www.bancaditalia.it/pubblicazioni/rapporto-stabilita/2011-2/1-Financial-Stability-Report.pdf?language_id=1.

[7] More precisely, we considered those loans outstanding at the end of 2001 - when the securitization market for performing loans started to develop in Italy - and those originated over the period 2002 to 2006. The Italian credit register provides information on credit exposure at the borrower-lender level. We use the term loan and credit exposure interchangeably.

Purpose Vehicle (SPV). As by law it is mandatory for SPVs to report the performance of securitized loans to the Bank of Italy Credit Register in the same fashion as is done with other non-securitized loans, we are able to continue tracking the securitized exposures' quality and repayment dynamics even after they disappear from the originating banks' balance sheets.

We augment these data with information on bank and firm characteristics. The former is drawn from the Bank of Italy Supervisory records and provides quarterly information on all balance sheet items. Information for firms is instead obtained from the proprietary database Cerved, which collects balance sheet information for a representative sample of non-financial corporations at a yearly frequency. Firms for which we do not have such specific balance sheet information (mainly sole proprietorships or producer households) are considered more opaque than the others and are used in specific robustness tests.

Due to computational reasons, we analyse a random subsample of the entire dataset, resulting in a panel that includes about 66,000 firms and 700 banks, totalling 6.9 million bank/loan observations.[8] Mirroring the large presence of SMEs in the Italian economy, in our sample about 97 per cent of the firms for which we have balance-sheet information are SMEs (this is based on the definition of the European Commission, which identifies as SMEs those firms with total assets lower than 43 million euro; see also panel (a) in Figure 1 that describes the composition of our database by size). Firms for which we cannot obtain balance-sheet information from Cerved are not corporations, but other legal entities, typically very small. Indeed, about half of our sample is made of sole proprietorships or producer households (see

[8] The entire dataset includes about 880,000 firms. Before randomizing, we drop observations related to loans originated by non-banks and other loans for which we miss key information, such as observations related to loan sales to institutions not required to report to the Credit Register. Note that the fixed-effect regressions analysis will be conducted only on the sample of firms with multiple bank relationships, which amounts to 3.2 million. The estimation sample size is limited to 1.9 million observations for those specifications where we use firms' balance sheet information, as these are available only for firms present in the Cerved dataset (about half of the firms that we have in the sample).

panel (b) in Figure 1).

Turning to the securitization deals, on average about 8 per cent of the firms had at least one loan securitized over the period considered; this amounts to 4 per cent of the existing exposures. Looking at banks, we cover almost all domestic intermediaries operating in Italy. Of these, however, 50 intermediaries have been active in the securitization market, along with about 60 SPVs. Table 1 reports a few key summary statistics for both banks and firms.

As we are interested in the securitization decision and in loan quality developments (at the time of securitization and afterwards), we model two main dependent variables that capture, respectively, the probability that a loan is securitized and the probability that the quality of the loan deteriorates. In the baseline regression, the former is a dummy variable that takes value one when the firm is securitized, the latter is also a dummy, which becomes one when the exposure becomes at least 90 days past due or worse.

Figure 2 displays the developments over time in the credit quality of loans, sorted into securitized and not, by plotting for each group the monthly mean of performing (not deteriorated) exposures.[9] As can be seen, both categories display a deteriorating trend that reflects the outbreak of the global financial crisis first and the sovereign crisis afterwards. However, securitized loans, if anything, seem to perform better than non-securitized ones.

[9] The small discontinuity in December 2005 is related to a change in the reporting of NPLs to the Credit Register (non-performing loans other than bad loans were not required to be identified prior to this date).For robustness purposes, we then also analyze the probability of a firm's default, which is not affected by such discontinuity.

4. The estimation strategy

To identify how securitization of loans is affected by information asymmetry, we adopt the approach taken by Chiappori and Salanié (2000) in their seminal study of insurance markets.[10] We surmise that securitization is affected by asymmetric information if – accounting for a set of characteristics observable to investors in securitized loans − there is a positive correlation between the securitization of loans and the probability that these loans deteriorate into non-performing.

Indeed the probability of securitization and deterioration of a loan granted to firm *f* by bank *b* at time *t* can be assumed to depend on a set of characteristics, θ, which represent the information set of the investors (in the ABS):

$$\mathrm{Prob}\left(\mathrm{Securitization}_{fbt} = 1 \middle| \theta_{fbt}\right) = F_s\left(\eta\theta_{fbt} + \varepsilon_{fbt}\right) \tag{1}$$

$$\mathrm{Prob}\left(\mathrm{Deterioration}_{fbt} = 1 \middle| \theta_{fbt}\right) = F_D\left(\eta`\theta_{fbt} + \varepsilon`_{fbt}\right) \tag{2}$$

ε_{fbt} and $\varepsilon`_{fbt}$ are the error terms, and the sign of the correlation between them provides, as in Chiappori and Salanié (2000), a test of the presence of information asymmetry:

$$H_0\!: Corr\left(\varepsilon_{fbt}, \varepsilon`_{fbt}\right) > 0 \tag{3}$$

We augment this approach to disentangle adverse selection from moral hazard. We start from the premise that selecting versus monitoring of borrowers by a lender may affect the other financiers differently. Borrower selection will affect *all financiers* almost equally while borrower monitoring by its very nature will involve and affect mainly *the monitoring lender*. Indeed, think of borrower selection as assessing the borrower's characteristics which are

[10] The methodology we apply to detect the relevance of asymmetric information effects is inspired by the similarity between the securitization market and the insurance market, as they both transfer risk across agents in the economy. For more information on the application of the Chiappori and Salanie methodology to the securitization market, see Albertazzi et al. (2015).

relevant for the risk of *all* exposures, such as the borrower's recent loss of market share in product markets or failure to succeed in procurement tenders. This assessment will determine the probability of default on all ensuing exposures. In contrast, borrower monitoring will have the involved lender undertaking due-diligence activities that will mainly increase the likelihood of repayment of the *own* outstanding loan.

Our identification strategy holds under rather general assumptions about both the presence of spillovers of monitoring activity on the risk borne by other creditors of the same borrower and the reactions that these may exhibit in response to such spillovers. The possibly most problematic case is where monitoring is a public good so that a reduction in monitoring by one bank (for instance, due to a securitization operation) implies, everything else equal, an increase in the risk faced by the other creditors exposed to the same borrower. Ruling out the (extreme) scenario where changes in the intensity of a given creditor's monitoring activity increase the risk borne by other lenders by the same amount, it will always be true that a reduction in monitoring activity is reflected in an increase in default risk, which is stronger for the bank that ceases monitoring. Such differences are exacerbated by the endogenous reaction of non-securitizing banks in case they observe that a securitization has taken place, which is the case in our dataset.[11]

Specifically, we decompose the error term (ε_{fbt} and $\varepsilon`_{fbt}$) into two components, i.e., firm-time fixed effects ($\alpha_{ft}$ and $\alpha`_{ft}$) and the remaining error (μ_{fbt} and $\mu`_{fbt}$):

[11] It can be easily formally shown that, under some mild regularity assumptions on the monitoring-cost function, non-securitizing lenders will react by increasing monitoring activity so as to (only) partially offset the increase in risk they face due to the drop in monitoring by the securitizing bank. In case of negative spillover, changes in monitoring cause (large) differences in the risk faced by the different creditors, so our identification approach is even more applicable. It is true that the reaction of non-securitizing banks will tend to mitigate the difference, but, again, it can be easily shown that under some mild regularity assumptions it will do so only (very) partially.

$$\varepsilon_{fbt} = \alpha_{ft} + \mu_{fbt} \tag{4}$$

$$\varepsilon`_{fbt} = \alpha`_{ft} + \mu`_{fbt} \tag{5}$$

We do so in order to assess separately the following two null hypotheses:

$$H_0(1): Corr(\alpha_{ft}, \alpha`_{ft}) > 0 \tag{6}$$

$$H_0(2): Corr(\mu_{fbt}, \mu`_{fbt}) > 0 \tag{7}$$

The first null hypothesis assesses if there is a positive correlation between the securitization of loans and the probability that these loans deteriorate into non-performance due to unobservable firm heterogeneity at origination and over the ensuing life of the loans. The second null hypothesis assesses if there is a positive correlation between the securitization of loans and the probability that these loans deteriorate into non-performing due to any remaining unobservable bank-firm specific heterogeneity. The former test of correlation can be readily interpreted as pertaining to the pervasiveness of information asymmetry when selecting borrowers, i.e., resulting in adverse selection; the latter test similarly to when monitoring borrowers, i.e., resulting in moral hazard.

As observable risk is likely to be both relevant for the choice of coverage level (for instance, because the pricing of the insurance scheme is typically conditional on observable characteristics) and correlated with unobservable risk, one important condition that needs to be satisfied when testing for asymmetric information is that all characteristics observable by the insurer (the investors in the ABS) and relevant for the risk profile are duly controlled for and, conversely, that the characteristics not observable by the insurer are excluded from the vector of controls. The latter, by definition, includes the soft information, but it also includes all possible pieces of hard information that cannot be conveyed to the market by the insured party – in our case, the originator.

Our baseline assumption is that the investors observe all time-invariant characteristics of the securitized firms, as well as all those, time-varying and invariant, of the originating bank. This amounts to assuming that θ_{fbt} includes a set of dummy variables d_f^F, one for each firm in the sample, and d_{bt}^B, one for each bank*month pair in the sample. To accommodate this in the estimation, we fit a linear probability model for the probability of securitization and for that of deterioration, saturating them by including bank*month, and firm or firm*month fixed effects. The latter and the residuals are used to test $H_0(1)$ and $H_0(2)$ represented in equations (6) and (7). The bank*month and the firm fixed effects instead capture the investors' information set. We discuss below the extent to which our conclusions can be considered sensitive to this choice.

This setup also allows us to test for the more general null hypothesis that there is a positive correlation between the securitization of loans and the probability that these loans deteriorate into non-performing based on the (time invariant) characteristics observable by the investors:

$$H_0(3): Corr\left(\eta_f, \eta`_f\right) > 0 \tag{8}$$

where η_f is the vector of the estimated coefficients for the dummies d_f^F in equation (1) and $\eta`_f$ is the corresponding vector for equation (2). Rejecting this null would indicate that there is instead an efficient selection in the loans to be securitized based on observable characteristics. Assessing the nature of the selection of the loans to securitize based on observables is important to gauge the overall degree of distortion in the securitization market. In fact, it could be, and it will turn out to be the case in our data, that while the tests detect asymmetric information, this effect is fully compensated by an efficient selection on loans to be securitized based on observables, rendering the unconditional quality of securitized loans significantly better than that of non-securitized ones.

In the next section, we report and discuss these three correlation coefficients and their statistical significance levels for a variety of specifications (that allow us to control for different hypotheses on the information set investors have).

5. Results

5.1. Baseline results: Selection, adverse selection and moral hazard

As described in the previous section, the three tests that we have designed will inform us respectively on: (i) the type of selection occurring on firms' characteristics observable by investors; (ii) the presence of adverse selection; and (iii) the presence of moral hazard. In our baseline setup, the information set of the investors covers the time-invariant characteristics of the firms (time invariant fixed effects), as well as those of the originating banks (bank*month fixed effects).

For the whole sample, we document a negative and significant correlation between the firm fixed effects from the two regressions ($H_0(3)$: $Corr(\eta_f, \eta`_f)$), suggesting that there is a positive selection going on at the level of firm observable characteristics (Table 3, panel (a), column (i)). In other words, borrowers that are more likely to be securitized - on the basis of such time-invariant features - are also less likely to deteriorate. At the same time, in column (ii) we observe a positive correlation between the firm time-varying fixed effects ($H_0(1)$: $Corr(\alpha_{ft}, \alpha`_{ft})$) indicating that we cannot reject the null of adverse selection. Regarding the correlation between the residuals ($H_0(2)$: $Corr(\mu_{fbt}, \mu`_{fbt})$), this is instead negative and significant. This indicates that overall there is no moral hazard from part of the banks after the securitization (see column (iii)); the somewhat counter-intuitive and negative sign of the coefficient is analysed in more detail and discussed below in this section and in Section 5.2.

The robustness of the above results has been tested in a number of ways. First, we cluster the correlations at various level (firm, originating bank, firm*time, originating bank*month). All tests continue to deliver significant results (results not shown).

Second, we tackle the concern that the loans we observe in our sample are both left and right censored, in the former case because we do not observe the date of loan origination if this is before 1997:12, and in the second because we stop tracking the loans in 2011:12. To address this, we estimate the correlation on the subsample of loans originated after 2001:01, and on that of loans for which we observe the conclusion (either repaid or defaulted) before the end of the sample. The baseline results carry over (see panels (b) and (c) in Table 3).[12]

Next, we swap the deterioration dummy with a default dummy, which takes value one only if the exposure is defaulted upon: also in this case, we document a positive selection at the level of firms' observable characteristics, the presence of adverse selection and the absence of moral hazard (see panel (d) of Table 3). Interestingly, the magnitude of the correlation between the time-varying fixed effects doubles.

Our conclusions are reached under the assumption that the information set of market investors includes structural (time-invariant) characteristics of the firms. It has been argued that this is a reasonable assumption; nonetheless, it is useful to assess the sensitivity of our findings to it, also in relation to the results obtained so far. From this perspective, it should be pointed out that our findings on moral hazard hold independently of it (rather, they depend on the

[12] In Section 5.5 we fit a number of survival models for the probability to enter into the deterioration status. This exercise can also be viewed as testing for censoring. Results are unaffected.

assumption that monitoring creates a wedge among the default risk faced by different creditors of a given borrower).[13]

The quantification of adverse selection – and therefore of total asymmetric information – instead relies by construction on what is assumed to be included in investors' information set. In this respect, we can point out that synthetic indicators of default risk, such as the rating, are available for some of the firms from the business register and in principle can be accessed by the originating banks or the investors. However, for more than two thirds of the firms in our sample these time-varying characteristics are just not available to investors, and not even reported in business registers. This offers strong grounds to consider our assumption that investors observe all structural characteristics of firms rather conservative. If anything, we need to test that it is not too optimistic, in that it concedes too much to investors' knowledge about the loans. In this respect, we show below that our conclusions are robust to a specification in which we consider a smaller information set, including only some of the structural (time-invariant) characteristics (Table 4).[14]

Given that our identification strategy relies on the estimation of fixed effects to model investors' information set and to disentangle adverse selection and moral hazard, we are bound to employ a linear probability model. Otherwise, the dichotomic nature of the two dependent variables would indicate that we should estimate a pair of probit equations rather than linear models. With this in mind, we present the probit estimates in Table 4. These estimations are run to check the robustness of the results to the adoption of a linear model. Ideally, to do so,

[13] The results for the total correlation, that is, based on both observable and unobservable characteristics (which we will present in Section 5.4), are by definition also independent from the assumption about investors' information set, meaning that all main policy implications are unaffected by it (overall, securitised loans are better than non-securitised ones).

[14] Although this is shown for the specific case of the bivariate probit system, the same holds for linear models (results not shown).

one would replicate the same regressions, changing the model but keeping everything else constant. In our context, however, this is not fully possible, precisely because these non-linear models do not allow to accommodate large sets of fixed effects. Thus, to control for the investors' information set, we have to approximate the approach followed above without resorting to the introduction of fixed effects. For what concerns banks' characteristics, we suppose that investors observe a number of balance sheet variables for the originating banks (these controls replace the banks time-varying fixed effects). For what concerns micro-level information on the characteristics of the firms, in line with the notion that investors observe their structural (time-invariant) characteristics, we include one dummy for large corporates, age, together with its quadratic term (as common in the empirical literature), and the rating (median rating over in the sample period).[15]

One side-benefit of this exercise is that, by having some meaningful variable as regressors, we can get some information on the determinants of the likelihood that a loan is securitized and that it deteriorates, although still in a reduced form context. In particular, the firms' rating appears to play a prominent role: firms with worse ratings are simultaneously less likely to be securitized and more likely to deteriorate. Banks with a higher capital ratio, which in our sample are for the large part small mutual banks, are associated with loans less likely to be securitized but more prone to deterioration. The same is true for larger banks and banks with a high share of deteriorated loans in their portfolio. The higher the funding gap, the higher the two probabilities. This suggests that banks with little deposits relative to their loan portfolio may try to tackle funding needs by relying more heavily on securitization. This may lead them to sell marginally riskier loans, though at a larger discount. The increasing and concave function of age that is estimated for both equations suggests that the probability that the two events may

[15] Although age is not time-invariant, we include it in the information set as it evolves deterministically.

occur is always positive, but decreasing with the age of the loan. Loans to large firms are less likely securitised, possibly reflecting the fact that a pool of loans backing an ABS is typically made of a large number of homogenous small loans, so that the idiosyncratic risk is fully diversified away. The negative coefficient in the equation for the probability of deterioration of the large firm dummy size simply reflects the intrinsic smaller risk involved by exposures to these borrowers.

The crucial parameter estimated is the rho coefficient (i.e., the correlation coefficient between the residuals of each of the two probits). Its statistical significance and its positive sign are consistent with what found in the previous linear estimation, documenting the presence of asymmetric information (adverse selection and moral hazard together).

5.2. Heterogeneity of the effects

Results could be driven by specific characteristics of the sample. We have therefore tested the robustness of the results by investigating possible heterogeneity in the effects in specific subsamples. The first test was to estimate the correlations by weighting observations by the exposure of the originating bank to the borrowers (Table 5 panel (a)). While both the efficient selection on firm observables and the evidence of adverse selection are confirmed, we can no longer reject the presence of moral hazard (column (iii)).

The finding that the securitizations of larger loans are characterized by a higher degree of moral hazard is suggestive of a transaction/relationship lending narrative. Large securitizations stem typically from large loans, which in turn are often of the transactional type, since they are granted to large firms, transparent enough not to need a close relation with an intermediary to access the credit market. At the same time, such relations, in virtue of the substitutability between various intermediaries, are less stable and durable, weakening banks' incentives to perform accurate monitoring, especially once the loans are sold to market investors. In particular, the level of monitoring can be expected to be lower than that exerted on relationship borrowers, which not only are more opaque, but are also more likely to establish long-term credit relations with a small handful of intermediaries.

We test our conjecture by comparing the correlations for subsamples of firms that are sorted according to dimensions typically associated with relationship-type and transaction-type lending. First, we sort firms into small and large firms, separating SMEs (with total assets below 43 mln euro) from larger firms. Table 4 (panels (b) and (c)) displays how moral hazard cannot be detected for the former group, while it is present in the latter. Next we look at firms that differ in the share that is granted to them by their main bank. In particular, we consider transaction firms those whose main share is below the median of the share's distribution. Figure 3 shows how this sorting identifies well the larger firms. The results in panels (d) and (e) of Table 5 again demonstrate that the presence of moral hazard can only be found for transaction-type borrowers.

The same finding is confirmed, although only qualitatively, when we separate borrowers according to their average number of lenders, to classify as relationship firms (transaction firms) those who have less (more) than five lenders (99th percentile of the distribution; see panels (a) and (b) in Table 6). Figure 4 displays the distribution of average number of lenders by firm size.

On the contrary, when we sort firms according to the (so called functional) distance between from the bank's and the firm's headquarters, another variable that has been used in the literature to distinguish transaction from relationship lending (Alessandrini et al., 2009), we cannot document a difference in the intensity of moral hazard between the two groups (panels (c) and (d) in Table 6). However, distance is captured by a dummy denoting bank-firm pairs in the same province. As can be seen in Figure 5, being located in the same province is not a very precise proxy for relationship/transaction types of credit. Nonetheless, we will see that once we consider all these characteristics together, distance will also play a role.

5.3. Multivariate analysis

To further corroborate our conjecture that the nature of the credit relation matters for the degree of moral hazard, we adopt a multivariate strategy that consists of regressing the error term from the regression for the probability of deterioration on that obtained from estimating the probability of securitization, interacted with a number of regressors capturing the dimensions along which we split the sample in the previous section. This procedure allows us to test all the findings in a multivariate setting, which improves on the approach used so far by testing all the dimensions simultaneously rather than proceeding by sample split.

Table 7 displays the results, employing in the three columns three different clusters for the residuals (firm*month, firm*quarter and firm*year). First, note that the direct correlation between the two residuals is negative and significant and approximately of the same magnitude of that estimated for the baseline correlations in the univariate setting. This confirms that overall there is no evidence of moral hazard. Next, see how the interaction between the residuals for the securitization regression with all three transaction-lending variables that we consider (large firms, low maximum share, high number of lenders) are positive and significant, indicating that for these transaction type relations there is evidence of (more) moral hazard. In this context, the interaction with the dummy for relationships that are in the same province also becomes negative, indicating that relationship lending (captured by lower distance) further attenuates the moral hazard.

The last two columns of Table 7 include two additional variables, the age of the bank/firm and the amount of risk actually transferred by the securitizing bank (and the corresponding interactions with the residuals of the securitization equation). All the coefficients discussed above remain stable to this inclusion. The interaction with age is negative and significant, indicating that the degree of moral hazard is lower for borrowers that are securitized by banks with which they have a longer history. On the contrary, that with the share of risk transferred is positive and significant, documenting that the ampler the risk transferred, and, conversely, the lower the skin in the game retained, the higher the presence of moral hazard.

5.4. Assessing the total effect

The last step of the analysis is to calculate the overall effect of asymmetric information and the total informational effect (including that stemming from the selection of loans based on the observables) on the securitization market. To this end, we return to the univariate tests carried out for the baseline specification (Table 3, panel (a)) and estimate the correlation for the sum of the time-varying effects (adverse selection) and the error term (moral hazard). In both the unweighted (Table 8, panel (a), column (iv)) and weighted case (Table 8, panel (b), column (iv)), this correlation is positive and significant, suggesting that there is asymmetric information at play in the market.

At the same time, we find that the correlation between all the fixed effects and the error term is negative and significant (Table 8, panels (a) and (b), column (v)). This finding demonstrates that the information asymmetry distortion is more than compensated by the positive selection effect that takes place at the level of firms' observable characteristics; rejecting the view that securitization lead to laxer credit standards.[16]

[16] In principle, in these regressions we have an issue of generated regressors which may lead to inflated levels of statistical significance. At the same time, with almost 2 million observations, this issue can safely be neglected.

5.5. Duration models

The relationship between securitization and deterioration can be approached also through the lens of duration analysis, modelling the impact of securitization on the time a loan takes to deteriorate.

The main advantage of duration models, compared to the panel regression approach adopted so far, is that they are explicitly conceived to handle data describing the time to an event, which is very natural way to think of the notion of a loan "becoming" deteriorated and/or securitized. Relatedly, compared to the linear probability setup, duration models can take into account the effect on the estimates of the presence of censored observations, which in our context are represented by all loans that do not deteriorate before the end of the sample period.

One drawback of this type of analysis is that, applied to the context at hand, it can essentially exploit only the cross-section of the data. In a duration approach, in fact, the unit of observation remains the bank-borrower pair; however, the dependent variable becomes the time to the deterioration for such pair and the explanatory variables are characteristics of the bank-borrower match which, differently from what happens in the panel framework, cannot have a time dimension. This is a considerable limitation in view of the identification approach that we have followed so far. For instance, in our baseline setup, we assumed that investors observe all time-invariant characteristics of the borrowers, captured by the firm fixed effects, but not the time-varying ones, estimated by the firm*month fixed effects. It follows that, given this assumption and the constraint to cross-sectional data, we can use duration modeling techniques only to estimate the total informational effect on the securitization market. In fact, we will be able to control for individual banks' characteristics via the inclusion of bank-specific dummies; accordingly, the coefficient for the securitization dummy can be interpreted as capturing the overall informational effect (i.e., the effect of asymmetric information including the impact stemming from the selection on loans based on observables).

Since data inspection has shown that the variable $securitization_{fb}$ fails to comply with the proportional hazard assumption, we opt to estimate a number of parametric accelerated failure time models. These model the log of survival time rather than the hazard ratio and require distributional assumptions on survival time to be made.[17]

Specifically, we estimate via maximum-likelihood the effect of $securitization_{fb}$, a dummy that takes value one if the relationship between bank *b* and firm *f* is securitized, on the logarithm of the bank-firm match's time (in months) to deterioration $ln(\mathrm{t}_{fb})$,

$$ln(\mathrm{t}_{fb}) = securitization_{fb}\beta + \omega_b + u_{fb} \tag{9}$$

including bank dummies ω_b; errors are clustered at the firm level.

Table 9 presents the estimates of model (9). As results are displayed in the accelerated failure metric, a coefficient larger (smaller) than zero indicates that an increase in the corresponding regressor is associated with a longer (shorter) survival time or, equivalently, with a smaller (larger) hazard rate. The coefficient for $securitization_{fb}$ is always above zero and significant, irrespectively of the distributional form assumed (which are the exponential, the Weibull, the log-normal and the log-logistic in columns i, ii, iii and iv respectively), indicating that securitized loans tend to deteriorate at a lower frequency than non-securitized ones. This finding is robust to the inclusion of bank dummies, for all the distributions considered (columns v to viii). According to these estimates, and under the reduced-form model estimated here,

[17] We consider the Weibull, exponential, log-normal and log-logistic distributions, and run tests for model selection.

securitized loans deteriorate at on average a 58 per cent lower rate than non-securitized loans. This result is presented graphically in Figure 6, which displays the survival experience for a subject with a covariate pattern equal to the average covariate pattern, obtained when assuming a Weibull distribution (and controlling for bank dummies).[18] This result corroborates the evidence discussed in Table 7, in which we document the absence of the total informational effect in the securitization market.

6. Conclusions

Restarting the market for ABS backed by SME loans could have a sizeable impact on loan supply (Aiyar et al. 2015). In June 2014 the stock of outstanding SME securitization in Germany, France, Italy and Spain was €57 billion, compared to banks' outstanding SME loans of €849 billion. In other words, just above 5 per cent of SME loans were securitized. This paper addresses the question of whether attempts to revitalize this market are advisable, or if this type of product is inherently flawed by distortions arising from asymmetric information.

Using a unique dataset including a representative sample of Italian firms, we have analyzed the impact of asymmetric information in securitization deals for small and medium-sized enterprises. By building on a methodology previously applied to insurance data that looks at the correlation between risk transfer and default probability, we develop an empirical strategy to disentangle moral hazard from adverse selection problems.

Our results indicate that in Italy the securitization market for SME loans worked smoothly, though with some heterogeneity. We document the presence of asymmetric information, mainly in the form of adverse selection. Moral hazard is limited to credit exposures

[18] We have conducted a number of model selection tests to discriminate between the four distributional assumptions. The Akaike information criterion favors the Weibull distribution, which assumes increasing hazard rates over time.

characterized by a weak relationship between the borrower and the lender, indicating that a tight credit relation is a credible commitment to monitoring after securitization. Importantly, the selection of which loans to securitize based on observables is such that it largely compensates for the effects of asymmetric information, rendering the unconditional quality of securitized loans significantly better than that of non-securitized ones. Thus, despite the presence of asymmetric information, our results are inconsistent with the view that credit-risk transfer leads to lax credit standards.

Our paper also allows us to derive some policy implications. The finding that securitization of larger, transaction-type loans is characterized by moral hazard suggests that for this segment of the market it could be efficient to implement precise regulations on minimum retention. For smaller firms, on the contrary, retention rules may not be advisable: since the main distortions stem from adverse selection, endogenously chosen levels of retention may allow banks to better signal the quality of their securitized loans. In this case, improving transparency by extending the availability of granular information may be more advisable.[19]

[19] Along these lines, see the loan level initiative by the ECB that increases transparency and makes more timely information on the underlying loans and their performance available to market participants in a standard format (https://www.ecb.europa.eu/paym/coll/loanlevel/html/index.en.html). The Analytical credit dataset of the ECB – AnaCredit initiative – develop a new international data base based on new and improved statistics (https://www.bankinghub.eu/banking/finance-risk/analytical-credit-dataset-of-the-ecb-anacredit).

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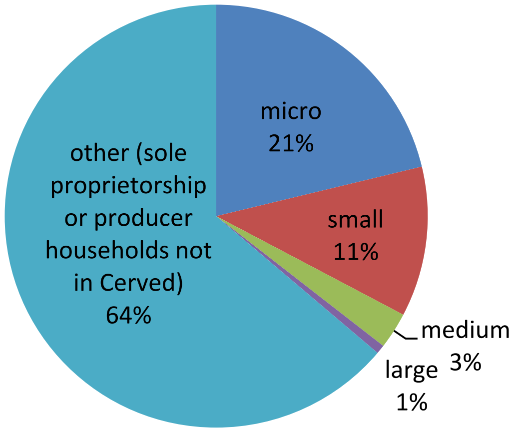
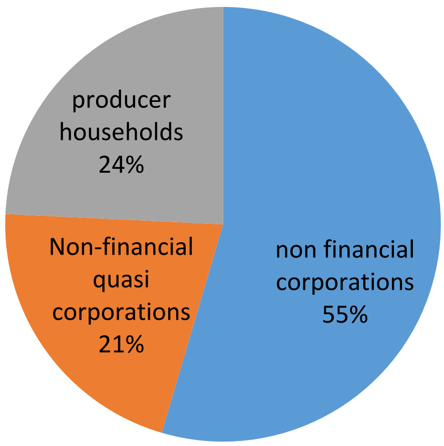
Figure 1. Composition of firms in the sample

Panel (a) – Distribution by size



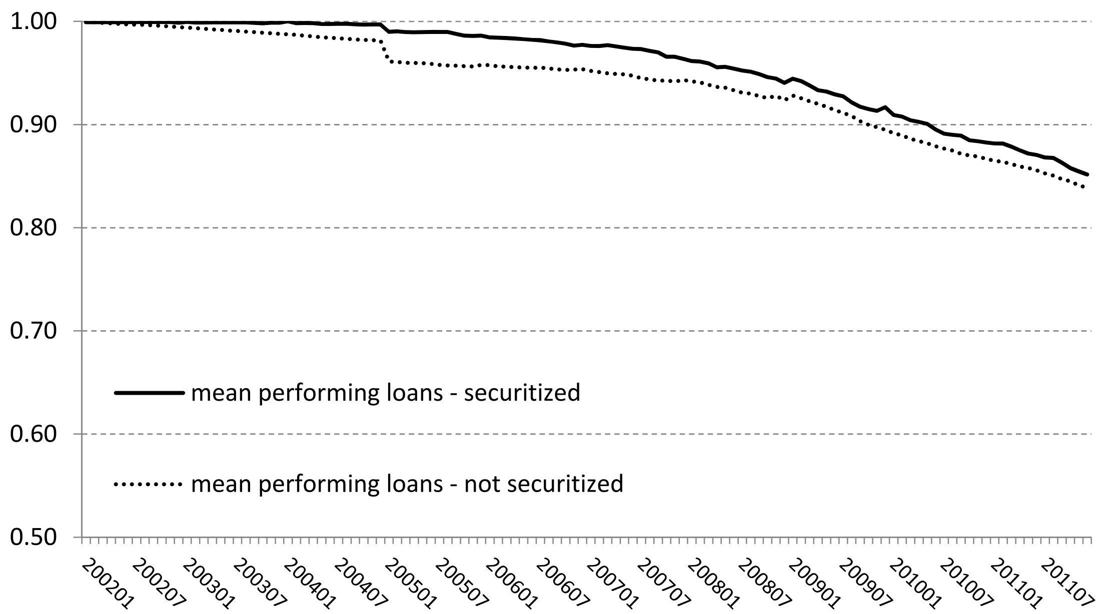
Note: Panel (a) reports the shares of micro, small and medium firms (SMEs) and that of large firms in the sample according to the EC definition based on their total assets: micro if with less than 2 mln. euro; small firms if above that and less than 10 mln. and medium if above that and less than 43 mln. Such information is not available for firms that are not surveyed in the Cerved registry, which is the case prominently for very small non-financial corporations or other legal entities typically very small as well.

Panel (b) – Distribution by legal entity



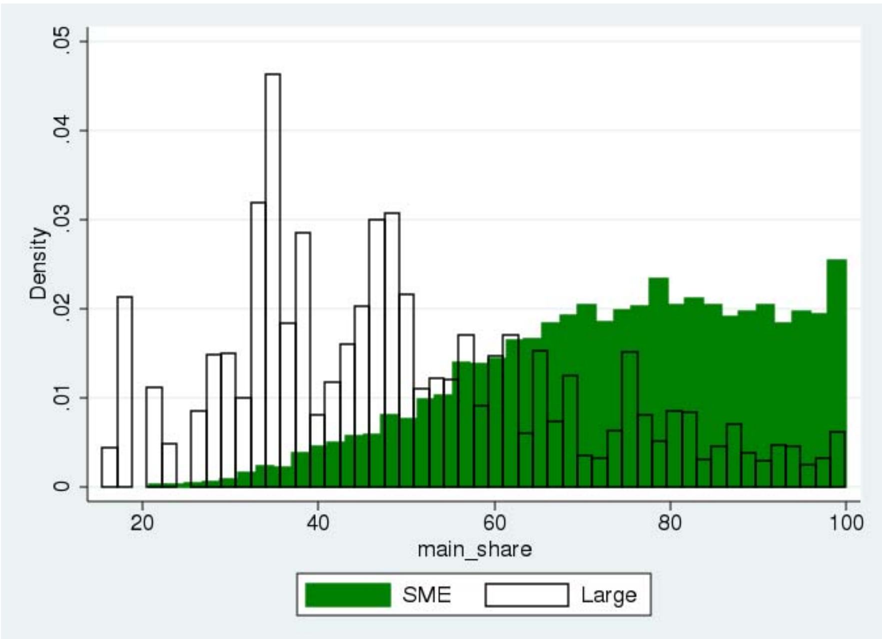
Note: Panel (b) reports the share of firms according to their legal entity. Differently from non-financial corporations, non-financial quasi corporations and producer households are entities without legal personality that draw up full financial statements and whose economic and financial operations are distinct from those of their owners. Non-financial quasi-corporations include general partnerships, limited partnerships, informal associations, de facto companies, sole proprietorships (artisans, farmers, small employers, members of professions and own-account workers); the category 'producer households' has five or fewer workers (see www.bancaditalia.it/pubblicazioni/ricchezza-famiglie-italiane/2014-ricchezza-famiglie/en_suppl_69_14.pdf).

Figure 2. Evolution of the quality of securitised/non-securitised loans



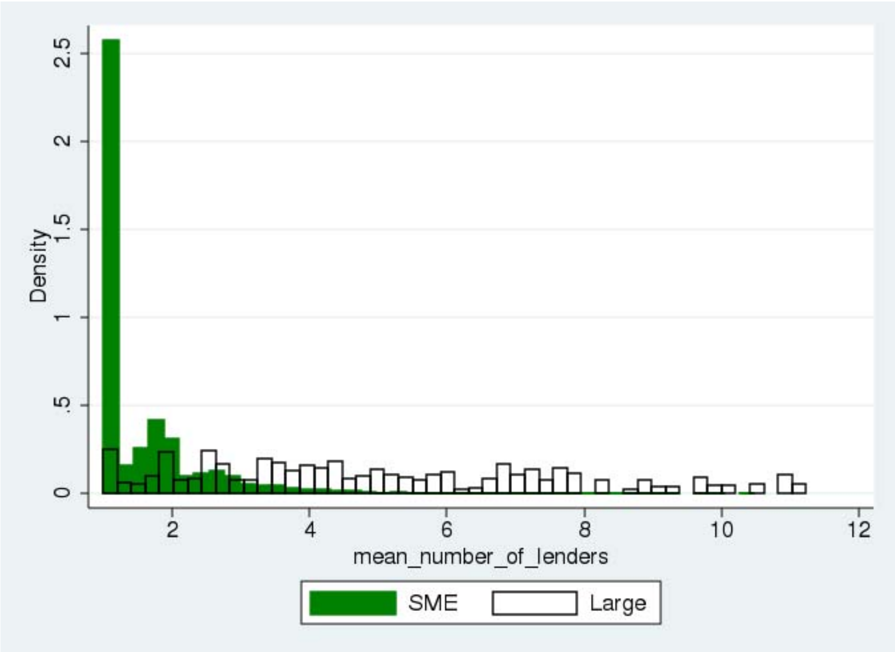
Note: The figure displays the evolution over the sample in the quality of securitized/non-securitized loans, as the percentage of loans that are performing over the total of loans that in each given month are securitized/outstanding.

Figure 3. Distribution of share granted by the main lender: SMEs vs large firms



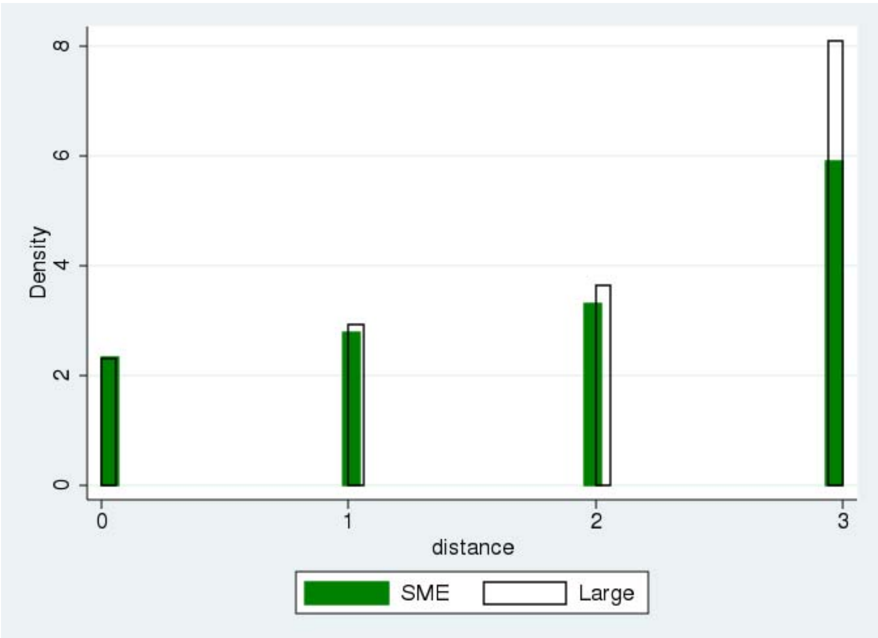
Note: The figure displays the distribution of share granted by the main lender (main share) against that of SME and large firms

Figure 4. Distribution of mean number of lenders: SMEs vs large firms



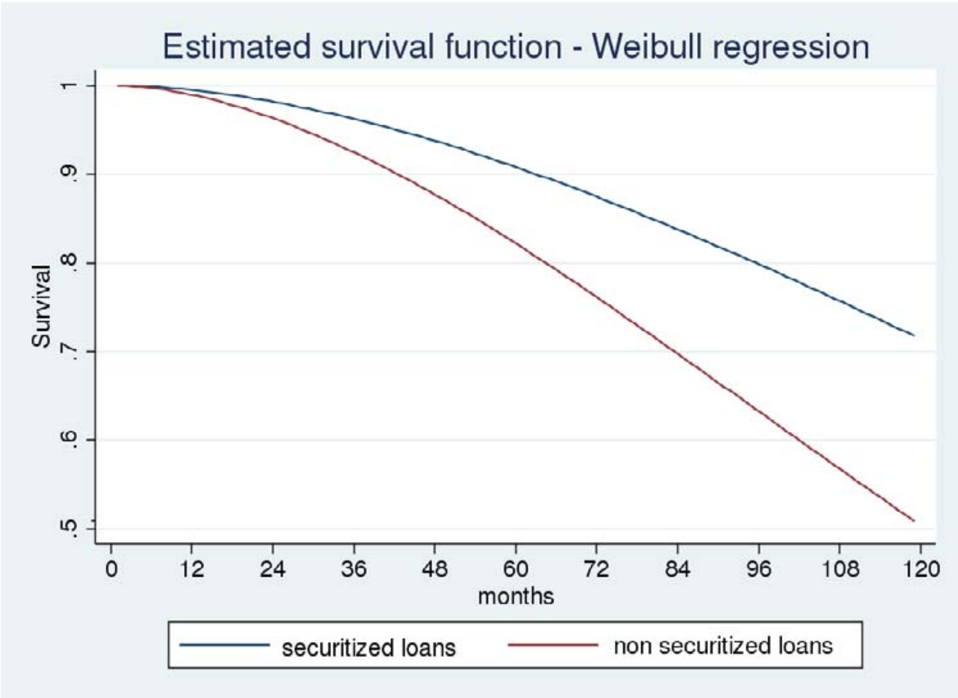
Note: The figure displays the distribution of mean number of lenders against that of SME and large firms.

Figure 5. Distance: SMEs vs large firms



Note: The figure displays the distribution of SME and large firms located respectively in the same province (distance=0); in the same region (distance=1); in the same macro-region (distance=2) and outside that (distance=3).

Figure 6



Note: The figure displays the survival experience for a subject with a covariate pattern equal to the average covariate pattern, obtained when assuming a Weibull distribution (and controlling for bank dummies; column 4 table 8)

Table 1. Summary statistics

a) Banks

	All banks				
	Mean	Median	Min	Max	Std. dev.
total assets (in log)	6.4	5.8	5.3	13.5	1.4
capital ratio (%)	14.6	13.8	1.3	261.7	8.5
liquidity ratio (%)	18.2	17.1	0.0	93.0	11.5
funding gap (%)	58.2	57.8	.01	100	15.0
impaired/tot loans (%)	3.3	2.2	0.0	88.6	12.8
Obs.	20023	20023	20023	20023	20023

	Only banks active in the securitization market only				
	Mean	Median	Min	Max	Std. dev.
total assets (in log)	9.5	9.4	5.9	13.5	1.9
capital ratio (%)	7.5	7.2	1.3	41.9	4.1
liquidity ratio (%)	12.9	10.9	0.0	76.7	126.1
funding gap (%)	72.7	61.5	24.8	100	12.7
impaired/tot loans (%)	3.8	3.3	0.0	20.5	5.6
Obs.	1185	1185	1185	1185	1185

Note: summary statistics for the bank balance sheets variables. Quarterly values, at the consolidated level

b) Firms

	All firms				
	Mean	Median	Min	Max	Std. dev.
Rating	7.8	5	1	9	15.2
Total assets	6.9	1.5	0.0	79.7	61.7
Net wealth	1.5	0.1	0.0	20.7	17.9
Self-financing	.32	0.0	0	5.5	4.6
Roe	-3.08	4.4	-306.5	155	64.5
Obs.	153994	153994	153994	153994	153994

	Only firms with at least a loan that has been securitized				
	Mean	Median	Min	Max	Std. dev.
Rating	6.6	5	1	9	11.5
Total assets	12.3	3.13	0.118	151.9	56.6
Net wealth	2.5	0.4	0.0	312.5	10.8
Self-financing	0.55	0.1	-2.5	325.5	4.1
Roe	-0.3	5	-270.6	153.6	58
Obs.	16369	16369	16369	16369	16369

Note: summary statistics for the firm balance sheets variables. Yearly values, at the consolidated level.

Table 2. Investors' information set

Variable	Description
Dummy large firm	dummy taking value 1 if the firm's assets are above 43mln euro
Dummy sole proprietorships, producing households	dummy taking value 1 if the firm's legal entity is that of a non-financial quasi corporation or a produced household
Age in years	is the number of years the relationship between the firm and the bank has been ongoing
Dummy bad rating	dummy that takes value 1 if the firm's rating is above the warning threshold
Total assets originator	log of originating bank's total assets
Capital ratio originator	originating bank's capital ratio
Liquidity ratio originator	originating bank's liquidity ratio
Funding gap originator	originating bank's funding gap
Share of impaired loans originator	originating bank's share of impaired loans over total loans

Note: description of the variables used in the robustness of the information set to alternative specifications.

Table 3. Results

	Selection on observables - firms (i) $H_{30}: Corr(\eta_f, \eta`_f)$	Adverse selection (ii) $H_{10}: Corr(\alpha_{ft}, \alpha`_{ft})$	Moral hazard (iii) $H_{20}: Corr(\mu_{fbt}, \mu`_{fbt})$
Panel (a): Baseline, whole sample	-0.0261***	0.019***	-0.0060***
Number of observations		3,179,615	
Number of Fixed effects		20,227	
Number of Firm*time FE		1,240,622	
Number of originator*time FE		59,184	
Adj. R-squared deterioration		0.6383	
Adj. R-squared securitization		0.4173	
Panel (b): Only loans originated after 2001:01	-0.0303***	0.0112***	-0.0042***
Number of observations		1,463,514	
Number of Fixed effects		11,654	
Number of Firm*time FE		605,424	
Number of originator*time FE		43,950	
Adj. R-squared deterioration		0.6143	
Adj. R-squared securitization		0.3992	
Panel (c): Only loans not censored	-0.0198***	0.0383***	-0.0035***
Number of observations		317,9615	
Number of Fixed effects		20,227	
Number of Firm*time FE		1,240,622	
Number of originator*time FE		59,184	
Adj. R-squared deterioration		0.6383	
Adj. R-squared securitization		0.4173	
Panel (d): Changed to probability of default	-0.0226***	0.0077***	-0.0035***
Number of observations		3179615	
Number of Fixed effects		20227	
Number of Firm*time FE		1240622	
Number of originator*time FE		59184	
Adj. R-squared deterioration		0.8522	
Adj. R-squared securitization		0.4173	

Note: Panel (a) reports the results of the two dimensional linear probability model (see equations 1 and 2) with on the right hand side firm and time varying and time invariant fixed effects. Panel (b)-(d) display the results obtained from the estimation of the same model using different subsamples. Correlations between the firm fixed effects ($\eta_f, \eta`_f$), the firm time-varying fixed effects ($\alpha_{ft}, \alpha`_{ft}$) and the residuals ($\mu_{fbt}, \mu`_{fbt}$) between the securitization of loans on the probability that these loans deteriorate into non-performance.

Table 4. Bi-probit without fixed effects

	(i) probability of deterioration	ii) probability of securitization
Dummy large firm	-0.194***	-0.068***
	(0.009)	(0.013)
Age in years	0.409***	0.226***
	(0.003)	(0.004)
Age in years^2	-0.027***	-0.016***
	(0.000)	(0.000)
Median rating over relationship	0.325***	-0.057***
	(0.001)	(0.002)
Total assets originator	0.008**	-0.038***
	(0.001)	(0.002)
Capital ratio originator	0.004***	-0.119***
	(0.000)	(0.001)
Funding gap originator	0.013***	0.061***
	(0.000)	(0.000)
Share of impaired loans originator	0.053***	-0.083***
	(0.001)	(0.001)
Total effect (rho)	-0.030** (0.005)	
Likelihood-ratio test of rho=0: Prob > chi2	0.000	
Observations	2,002,196	2,002,196

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5. Heterogeneity in the effects: weighted sample, firms' size and bank share

	Selection on observables - firms (i) H_{30}: Corr(η_f, $\eta`_f$)	Adverse selection (ii) H_{10}: Corr(α_{ft}, $\alpha`_{ft}$)	Moral hazard (iii) H_{20}: Corr(μ_{fbt}, $\mu`_{fbt}$)
Panel (a): Correlation weighted by the size of the banks' exposure to the borrower	-0.0295***	0.0158***	0.0083***
Number of observations		3,179,615	
Number of Fixed effects		20,227	
Number of Firm*time FE		1,240,622	
Number of originator*time FE		59,184	
Adj. R-squared deterioration		0.6383	
Adj. R-squared securitization		0.4173	
Panel (b): relationship lending (SMEs with total assets below 43 mln euros)	-0.0381***	0.0025***	-0.0061***
Number of observations		1,816,311	
Number of Fixed effects		9,582	
Number of Firm*time FE		679,305	
Number of originator*time FE		49,129	
Adj. R-squared deterioration		0.6165	
Adj. R-squared securitization		0.43	
Panel (c): transaction lending (larger firms, with total assets above 43 mln euros)	-0.1142***	0.0155***	0.0295***
Number of observations		109,280	
Number of Fixed effects		276	
Number of Firm*time FE		24,574	
Number of originator*time FE		11,277	
Adj. R-squared deterioration		0.4985	
Adj. R-squared securitization		0.683	
Panel (d): relationship lending firms (defined as those with main share above the median of the distribution)	-0.0226***	0.0194***	-0.0074***
Number of observations		2,814,707	
Number of Fixed effects		19,559	
Number of Firm*time FE		1,166,979	
Number of originator*time FE		57,695	
Adj. R-squared deterioration		0.6263	
Adj. R-squared securitization		0.416	
Panel (e): transaction lending firms (defined as those with main share below the median of the distribution)	-0.0305***	0.0161***	0.0043***
Number of observations		349,673	
Number of Fixed effects		661	
Number of Firm*time FE		71,871	
Number of originator*time FE		23,578	
Adj. R-squared deterioration		0.6943	
Adj. R-squared securitization		0.4465	

Note: Correlations between the firm fixed effects (η_f, $\eta`_f$), the firm time-varying fixed effects ($\alpha_{ft}$, $\alpha`_{ft}$) and the residuals (μ_{fbt}, $\mu`_{fbt}$) between the securitization of loans on the probability that these loans deteriorate into non-performance.

Table 6. Heterogeneity in the effects: number of lenders and informational distance

	Selection on observables - firms (i) $H_{30}: Corr(\eta_f, \eta`_f)$	Adverse selection (ii) $H_{10}: Corr(\alpha_{ft}, \alpha`_{ft})$	Moral hazard (iii) $H_{20}: Corr(\mu_{fbt}, \mu`_{fbt})$
Panel (a): relationship lending firms (defined as those with less than 5 lenders)	-0.0246***	0.019***	-0.0069***
Number of observations		2,889,901	
Number of Fixed effects		19,810	
Number of Firm*time FE		1,194,306	
Number of originator*time FE		57,701	
Adj. R-squared deterioration		0.6288	
Adj. R-squared securitization		0.4026	
Panel (b): transaction lending firms (defined as those with more than 5 lenders)	-0.0702***	0.0136***	0.0003
Number of observations		275,953	
Number of Fixed effects		414	
Number of Firm*time FE		45,426	
Number of originator*time FE		20,824	
Adj. R-squared deterioration		0.7091	
Adj. R-squared securitization		0.4789	
Panel (c): relationship lending firms (defined as those located in the same province of the originating bank)	-0.0149***	0.0103***	0.0008
Number of observations		256,819	
Number of Fixed effects		2,161	
Number of Firm*time FE		121,544	
Number of originator*time FE		31,019	
Adj. R-squared deterioration		0.5716	
Adj. R-squared securitization		0.283	
Panel (d): transaction lending firms (not in the same province of the originating bank)	-0.0326 ***	0.0183***	-0.0032***
Number of observations		2,091,192	
Number of Fixed effects		14,246	
Number of Firm*time FE		829,499	
Number of originator*time FE		37,042	
Adj. R-squared deterioration		0.647	
Adj. R-squared securitization		0.4368	

Note: Correlations between the firm fixed effects $(\eta_f, \eta`_f)$, the firm time-varying fixed effects $(\alpha_{ft}, \alpha`_{ft})$ and the residuals $(\mu_{fbt}, \mu`_{fbt})$ between the securitization of loans on the probability that these loans deteriorate into non-performance.

Table 7. Multivariate analysis

	Dependent variable:				
	Residuals deterioration (i)	Residuals deterioration (ii)	Residuals deterioration (iii)	Residuals deterioration (iv)	Residuals deterioration (v)
Residuals securitization	-0.009***	-0.009***	-0.009***	-0.004	-0.004
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)
Dummy large firm	0.000***	0.000**	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Residuals securitization*dummy large firms	0.029***	0.029***	0.029***	0.028***	0.027***
	(0.006)	(0.010)	(0.006)	(0.010)	(0.010)
Transaction lending (low maximum share)	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Residuals securitization* dummy low max. share	0.012***	0.012***	0.012***	0.013***	0.012***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Transaction lending (high number of lenders)	0.000***	0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Residuals securitization* dummy high number of lenders	0.004	0.004	0.004	0.003	0.003
	(0.004)	(0.006)	(0.004)	(0.006)	(0.006)
Relationship lending (same province)	0.001***	0.001*	0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Residuals securitization* dummy relationship lending	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Relationship lending (age of the relationship in year)				0.000***	0.000***
				(0.000)	(0.000)
Residuals securitization*relationship age				-0.001**	-0.001**
				(0.001)	(0.001)
Exposure transferred (moral hazard)					-0.000**
					(0.000)
Residuals securitization*exposure transferred					0.000**
					(0.000)
Cluster	Firm*month	Firm*quarter	Firm*year	Firm*quarter	Firm*quarter
Observations	1,943,165	1,943,165	1,943,165	1,943,165	1,942,842

Note: The regressions display the estimates obtained from regressing the residuals from deterioration probability on that to become securitized, interacting them with a number of regressors capturing dimensions related to relationship and transaction lending. Errors are clustered respectively at the firm*month, firm*quarter and firm*year level. Standard errors in parentheses, *** p<0.01,**p<0.05, * p<0.1.

Table 8. Total effect

	Selection on observables - firms (i) $Corr(\eta_f, \eta`_f)$	Adverse selection *(ii)* $Corr(\alpha_{ft}, \alpha`_{ft})$	Moral hazard (iii) $Corr(\mu_{fbt}, \mu`_{fbt})$	Total asymmetric information (iv) $Corr(\alpha_{ft} + \mu_{fbt}, \alpha`_{ft} + \mu`_{fbt})$	Total effect (v) $Corr(\eta_f + \alpha_{ft} + \mu_{fbt}, \eta`_f + \alpha`_{ft} + \mu`_{fbt})$
Total sample	-0.0261***	0.019***	-0.0060***	0.0036***	-0.0059***
Total sample: Weighted correlations (1)	-0.0295***	0.0158***	0.0083***	0.0138***	-0.0060***

Note: Correlations between the firm fixed effects ($\eta_f, \eta`_f$), the firm time-varying fixed effects ($\alpha_{ft}, \alpha`_{ft}$), the residuals ($\mu_{fbt}, \mu`_{fbt}$), the time-varying part of the firm fixed effects and the residuals ($\alpha_{ft} + \mu_{fbt}, \alpha`_{ft} + \mu`_{fbt}$) and the overall error component ($\eta_f + \alpha_{ft} + \mu_{fbt}, \eta`_f + \alpha`_{ft} + \mu`_{fbt}$) between the securitization of loans on the probability that these loans deteriorate into non-performance. (1) Correlations are weighted by the size of the exposure between the firm and the bank.

Table 9. Duration models

	Dependent variable: log(Survival time)							
	(i)	(ii)	(iii)	(iv)	(iv)	(iv)	(iv)	(iv)
Dummy securitization	0.382***	0.302***	0.382***	0.335***	0.491***	0.407***	0.504***	0.442***
	(0.036)	(0.028)	(0.030)	(0.028)	(0.042)	(0.032)	(0.034)	(0.032)
Observations	108123	108123	108123	108123	108123	108123	108123	108123
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Bank dummies	No	No	No	No	Yes	Yes	Yes	Yes
Distribution of the survival time	Exponential	Weibull	Log Normal	Log Logistic	Exponential	Weibull	Log Normal	Log Logistic

Note: Estimation of the overall effect of securitization on survival time (duration model). The hazard function is assumed to be distributed respectively as an Exponential, Weibull, log-normal and log-logistic in columns (1), (2), (3)and (4). Standard errors are reported in parentheses *** p<0.001, ** p<0.05, * p<0.1. Whole sample.

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