The impact of securitization on tail and systemic risk: evidence from the financial crisis

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Abstract

This research examines the effects of securitization on the bank's risk exposure both in terms of individual expected shortfall and marginal expected shortfall as measure of systemic risk. The relationship between securitization activity and tail risk, both for the individual securitizing banks and for the market as a whole, is especially relevant in light of the consequences for financial stability, revealed by the 2007-2008 financial crisis. Using a sample of Italian listed banks over the period 2000-2009, we find that securitizing banks have, on average, higher expected losses in case of extreme events. This adds new evidence on the main findings in the literature that focused on the evidence that risk transfer through securitization is relatively insignificant compared to the risk retained by the originating bank. We show that this risk retention is in terms of an increase of tail risk. We also find that securitization increases the probability of the analyzed banks to become "systemically" riskier, but we find no difference when comparing the pre-crisis with the post-crisis period. This suggests that the systemic exposures of these banks are still as high as before the crisis with severe implications for financial stability.

Keywords: securitization; expected shortfall; systemic risk; marginal expected shortfall

JEL classification: G01; G12; G21; G32;

1. Introduction

In recent years, banks have impressively increased their risk transfer activities, both through the use of credit derivatives, mostly in the form of Credit Default Swaps (CDS) that allow them to trade credit risks on a variety of exposures, and through the use of the securitization by means of which banks transfer pools of loans from their balance sheet to third-party investors.

This growth has been exponential also outside the US, recording strong growth rates in Asia and Europe (see European Central Bank, 2008b; Lejot et al., 2008), but the credit crisis that broke out in 2007 had a strong negative impact on the market with a large decline in securitization activity. The macro factors behind this expansion can be recognized in financial market globalization, technological and financial innovation, and the trend towards a more market-based financial system. At banking system level, the Basle II process prompted the implementation of more sophisticated pricing models for credit risk, implicitly leading to a further development of securitization activity (Berger et al., 2010).

It is worth of mentioning that the main reason behind the use of credit risk activity (CRT) is that banks use it to move risk to less fragile institutions and to diversify away from concentrated exposures. The severity and widespread of the current crisis indicate that these risk transfer activities have increased risks in at least some parts of the financial system, arising the question on how this credit risk transfer (CRT) has affected the banks that used it to transfer risk to third-party investors. Although in principle a properly done transfer of risk should reduce banks' risks (Instefjord, 2005; Wagner, 2007), it still remains an empirical question as to whether CRT increases or reduces a bank's risk exposure. On one hand, securitization and credit risk transfer techniques allow banks to shift risks outside their balance sheet as well as to achieve portfolio and funding diversification more easily (European Central Bank, 2008). On the other hand, CRT could also lead banks to take on additional and excessive risks whether by using the funding obtained from securitization to grant riskier credits or simply by acquiring credit risk more easily on the market. Banks may also end up being riskier because they fail to effectively transfer the risk. This may be because a bank keeps the riskiest tranche in a securitization, or because of guarantees (explicit or implicit) given to securitization vehicles.

The literature has widely investigated the securitization techniques and the main rationale behind the banks' decisions to securitize as to obtain additional funding, to transfer risk to third-party investors, to generate fee income, to manage profits, and to minimize regulatory capital requirements (among others, Allen and Carletti, 2006; Ambrose et al. 2005; Krahnen and Wilde, 2006; Jeffrey, 2006). This research focuses on the impact of securitization on banks' risk profile relating to risk transfer, particularly evident in the years prior to the financial crisis, where banks have dramatically increased their risk transfer activities.

In this research, we examine the relationship between securitization activity and banks' risk profile over the period 2000-2009 for a sample of Italian listed banks. The objective is to explore whether the securitization has effectively affected the risk exposure of the securitizing banks by transferring risk to third-party investors and, at the same time, whether the credit risk transfers within the overall banking system has increased securitizing bank's expected contribution to systemic crisis in the pre and post-2007 financial turmoil.

The most common measure of risk used by financial institutions is the Value at Risk (VaR) that focuses on the risk of an individual institution in isolation. It is simply defined as the maximum dollar loss within a specified confidence level (for an overview, Kupiec, 2002; Jorion 2006). Recent papers have stressed the limit of VaR measures, especially in the recent financial crisis because it failed to pick up potential "tail" losses in the AAA-tranches. Therefore, as a measure of firm level risk, we focus on Expected Shortfall (ES) because it is coherent and more robust than VaR. The ES is the expected loss conditional on the loss being greater than the VaR. However, even if this measure takes into account what happens in the bank's return "tail" losses distribution (extreme events), it still remains a single institution' risk measures. To investigate whether the credit risk transfers within the banking systems worsen the financial stability, we need to consider a proper measure of systemic risk. According to the classification in Brunnermeier, Crocket, Goodhart, Perssaud, and Shin (2009), a systemic risk measure should identify the risk to the system by "individually systemic" institutions, which are so interconnected and large that they can cause negative risk spillover effects on others, as well as by institutions that are "systemic as part of a herd." A group of 100 institutions that act like clones can be as precarious and dangerous to the system as the large merged identity (Adrian and Brunnermeier, 2009). We decide to adopt the Marginal Expected Shortfall (MES) defined by Achraya (2009) as a measure of systemic risk. MES is defined as a bank's average losses in the tail of the aggregate sector's loss distribution. Moreover, Acharya (2009) provides a theoretical justification for MES being one of the main determinants of the Systemic Expected Shortfall (SES). Therefore, by comparing the results on the individual banks' ES and MES, we try to investigate the "tail" effects of the securitization with respect to the single institution's risk profile and its expected contribution to systemic risk in terms of tail dependence with the market, respectively.

The research contributes to the empirical literature on asset securitization and bank risks in several respects. First, the time horizon under investigation allows us to shed a light on the relationship between securitization and banks' risk exposures including the crisis 2007-2009 so that we can explore potential changes in systemic risk after the crisis broke out. The turmoil has illustrated how securitization could lead to financial instability by contributing to an increase in the occurrence of banking crises. In fact, the question as to whether securitization increases or reduces a bank's risk exposure is especially relevant because one of the key consequence of this technique referred to its effect on risk sharing between banks and markets and thus, on systemic risk. In other words, the impact of securitization activity on a bank's incentive towards risk taking could have significant implications for financial stability (Rajan, 2005). At the moment, the effect of the credit securitization on financial stability remains an open issue, also regulators. The Basle Committee has revised the framework of Basle II and imposed from 2011 stricter requirements on securitization in terms of transparency, valuation and risk disclosure trying to overcome one of the main critics to the Basle II framework that was not sufficiently focused on systemic risk, but only on the limitation of each institution's risk seen in isolation.

Secondly, differently from previous literature that used the beta as a measure of systematic risk but also as a proxy of systemic risk, we use the expected shortfall (ES) as measures of the banks' risk exposure in the extreme events and the marginal expected shortfall (MES) as a measure of systemic risk. The difference between MES and beta arises from the fact that systemic risk is based on tail dependence rather than on average covariance so that it better fits the definition of systemic risk in terms of expected losses of each financial institution in a future systemic event in which the overall financial system is experiencing losses. To our knowledge there are no previous studies employing these risk measures referring to securitization.

Third, despite the importance of the Italian securitization market that from 2001 to 2006 has become the European country with the second-largest issuance volume after the UK, there is a research void on it compared to other European countries. Regarding the Italian securitization market, to date, Agostino and Mazzuca (2011) are the only authors who have analysed the securitization determinants in the Italian market. More in general, there are still few studies that refer to the specific European countries (Martinez-Solano et al., 2009, and Cardone-Riportella et al., 2010, both considering the Spanish market). In the light of these considerations, we believe it is worth to consider other geographical contexts with differently developed capital markets, different banking sector structures and, in the case of Italy, with specific systemic implications.

We find that securitizing banks have, on average, higher expected losses in case of extreme events than banks not active in this market. This adds new evidence on the main finding in the literature that showed evidence that risk transfer through securitization is relatively insignificant, compared to the risk retained by the originating bank. The results support the evidence that this risk retention implies an increase of tail risk. Moreover, we find that the relationship between securitization and ES was unaffected by the financial turmoil started in 2007 and that originating banks experienced higher systemic risk (MES) than others banks not active in this market, both in pre and post 2007-crisis

The remainder of the paper is organised as follows. In Section 2, we analyse the relevant literature. In Section 3, we describe the estimation framework, sample and data, and variables. In Section 4, we present and discuss the empirical analysis and its results. In Section 5, we describe the robustness tests and Section 6 concludes.

2. Literature review

Securitizing banks and systemic risk

For the purposes of this research, we review the studies focusing on the role that securitization has on the originator banks' risk-taking. This is the area where our research aims to contribute by analyzing the determinants of banks' risk changes and thus investigating whether securitization increases or reduces a bank's risk exposure.

It should be noted that a large number of empirical studies find evidence that risk transfer through securitization is relatively insignificant compared to the risk retained by the originating banks for various reasons. For example, Froot et al. (1993) find that better risk management allows banks to operate with riskier balance sheets. Cebonoyan and Strahan (2004) find that banks improving their ability to manage credit risk may operate with greater leverage and may lend more of their assets to risky borrowers. The results undertaken by Cardone-Riportella et al. (2010), who analyse the Spanish securitizing banks over the period 2000-2007, indicate that securitization may make banks less averse to a crisis situation because they can more easily liquify parts of their balance sheet, such as by doing additional CLO operations. Wagner (2007) shows that increased liquidity of bank assets, paradoxically, increases banking instability and the externalities associated with banking failures. This is because even though higher asset liquidity directly benefits stability by encouraging banks to reduce the risks on their balance sheets and by facilitating the liquidation of assets in a crisis, it also makes crises less costly for banks. As a result, banks have an incentive to take on an amount of new risk that more than offsets the positive direct impact on stability. Instefjord (2005) highlights that when a bank has access to a richer set of tools to manage risk, it behaves more aggressively in acquiring new risks. Jiangli et al. (2008) use US data for bank holding companies and find that banks active in the securitization market tend to have lower insolvency risk and higher profitability than banks not active in the securitization market. Rajan (2005) stresses that more market-based pricing exacerbates the incentive structures driving banks and institutional investors, which could (under extreme circumstances) lead to excessive risk taking behaviour.

Several authors examine the relationship between securitization and a bank's equity risk. Krahnen and Wilde (2006) report higher beta for banks after securitization activity. Using 73 securitization announcements of 27 banks in Europe between 1999 and 2002, Franke and Krahnen (2006) provide empirical evidence that banks' systematic risk increases due to securitization transactions. They suggest that the risk-reduction effect of securitization is undermined because banks reinvest the new liquid capital into riskier projects. Moreover, they propose that risk-reduction by means of securitization is determined by the technique of tranching the securitization's issues. Hence, a post-event increasing beta should result from the fact that the first-loss piece exhibits a higher probability of failure than less risky senior tranches being transferred to external investors. Hansel and Krahnen (2007) confirm the previous findings, showing that the credit risk transfer activity enhances the systematic risk (equity beta) of the issuing bank and that overall credit securitization increases the bank's risk appetite. Uhde and Michalak (2010) study securitization and systematic risk in the European banking sector, by analysing a sample of European listed banks over the period 1997-2007. They find that securitization has a negative impact on the banks' financial soundness, a positive impact on leverage and return volatility and a negative effect on profitability. Nijiskens and Wagner (2011) build up two separate dataset, one for CLO and another for CDS banks, and analyse the two sub-samples over the period 1997-2006. They estimate the relationship between credit risk transfer activities (CLO issues and CDS trading) by banks and the systematic risk measured by the issuer/trading banks' beta (using an augmented CAPM). Their results show that, after their first use of CLOs and CDSs, the betas of the issuer/trading banks increase significantly. Keys et al. (2010) note that securitized assets have a higher probability of default than assets with similar characteristics that are not securitized, consistent with lower screening efforts by banks.

Wu and Hong (2010) analyse asset securitization and banks' risk exposure focusing on a sample of U.S. bank holding companies over 2002– 2007 to investigate whether the market views asset securitization as increasing or reducing a bank's risk. They measure the market perceived risk in terms of banks' equity risk and distinguish between systematic and idiosyncratic risk. Contrary to earlier evidence that suggests securitization increases issuing banks' systematic risk exposures, their findings provide a different conclusion: the market seemed to view asset securitization as reducing banks' systematic risk exposure; the estimates of the implemented variance regression show no evidence of increasing idiosyncratic risk; larger banks tend to have higher systematic risk and lower idiosyncratic risk because of diversification.

A recent number of papers examine the financial stability's implication of securitization deriving from its effect on risk sharing between banks and market, and then the effect on the systemic risk. The 2007-2008 credit turmoil illustrated how securitization could lead to financial instability. For Shin (2008) securitization has proven to be deleterious from a financial stability standpoint because it allows banks to overextend their balance sheet (for a given level of capital) and lower their credit standards. Building on Allen and Gale (2004), Allen and Carletti (2006) show that credit risk transfer could produce a reduction of welfare through the creation of contagion in others. On the other hand, several papers stress the evident benefits deriving from securitization activity for the banking system, due to the opportunity to smooth out the risk among many investors as credit risk can be more easily transferred and potentially widely transferred across the financial system. Even if, the total risk remains within the banking sector, securitization allows banks to hold less risk simply due to diversification and more tradeability (Berget et al., 2010). The transfer of credit risk can produce a more efficient use of bank's capital and a reduction in the cost of raising capital for loan intermediation, leading in turn to a lower cost of credit (Duffie, 2007). However, credit crisis originated from the various ways through which banks have transferred credit risk in the financial system, revealing the potential contribution of securitization activity to financial instability in terms of an increase in the risk of the occurrence of banking crises. As evidenced by Nijskens and Wagner (2012), securitization may also increase systemic risk, even if banks' individual risk does not raise. Firstly, because securitization allows banks to shed idiosyncratic exposures, such as the specific risk associated with their area of lending. Secondly, because securitization typically also exposes banks to a bigger funding risk, which can be considered mostly systemic in nature as current events have shown since the markets for securitized assets and markets for funding those assets may collapse. The idiosyncratic share in a bank's risk may also be lowered because banks may hedge any undiversified exposures they may have by buying protection using CDS while simultaneously buying other credit risk by selling protection in the CDS markets. Banks may thus end up being more correlated with each other. This may amplify the risk of systemic crisis in the financial system

(Elsinger et al. (2006); Acharya and Yorulmazer (2007)) since it increases the likelihood that banks incur losses jointly (a situation experienced in the current crisis).

Systemic risk measures

In this section, we briefly review the standard risk measures used inside the financial firms. This review allows us to define some simple concepts that will be useful for the purposes of our analysis.

Two standard measures of firm level risk are Value-at-Risk (VaR) and Expected-Shortfall (ES). They both measure the potential loss incurred by the firm as a whole in an extreme event. Specifically, VaR is the most that the bank loses with confidence 1-α, that is, Pr ($R < - VaR_{\alpha}$) = α. The parameter α is typically taken to be 1% or 5%.

The Expected Shortfall (ES) is the expected loss conditional on the loss being greater than the VaR. It is computed as the average of returns on days when the portfolio's loss exceeds its VaR limit. Denote by *r* the day *t* return of a given index (*I*), the Expected Shortfall is defined as:

$$ES_t(C) = E_t(r_t^I \mid r_t^I < C) \quad (1)$$

where C is a known threshold. Expected Shortfall is thus a partial moment capturing the expected value of the lower tail of the index distribution (the threshold is generally defined to be negative, or equal to the Value-at-Risk (VaR) at a given confidence level). Notably, as shown by Acerbi and Tasche (2002), ES is a coherent risk measure according to the definition given in Artzner et. al (1999).

Given equation (1), Acharya et al. (2010) and Brownlees et Engle (2010) derive Marginal Expected Shortfall of company *i* as the derivative of the market Expected Shortfall with respect to company *i* weight in the market index and ultimately define MES as:

$$MES_{i,t}(C) = E(r_{i,t} \mid r_t^I < C) \quad (2)$$

where $r_{i,t}$ is the day *t* return of the bank *i*. The main rationale behind MES is that if we consider the Expected Shortfall of the overall banking system, by letting *r* be the return of the aggregate banking sector or the overall economy, then each bank's contribution to this risk can be measured by its MES.

In other words, MES can be defined as the expected equity loss per dollar invested in a particular bank if the overall market decline by a certain amount and it is computed as the average return of each bank during the 5% worst day of the market. We first note that MES has been originally proposed by Taasche (2000) and later used by Yamai and Yoshida (2002). One example of this approach is provided in Engle and Brownlees (2010). They show that the banks with the highest MES are the banks that contribute the most to the market decline. Therefore, those banks are the most important candidates to be systemically risky. Equity holders in a bank that is systemically risky will suffer major losses in a financial crisis and, consequently, will reduce positions if a crisis becomes more likely. MES measures this effect. It clearly relies on investors recognizing which bank will do badly in a crisis.

The literature on systemic risk is recent and can be broadly separate into those taking a structural approach using contingent claims analysis of the financial institution's assets (Lehar, 2005: Gray et al, 2008; Gray and Jobst, 2009) and those taking a reduced-form approach focusing on the statistical tail behaviour of institutions' asset returns. In particular, referring to this latter strand of the literature, Adrian and Brunnermeier (2009) measure the financial sector's Value at Risk (VaR) given that a bank has had a VaR loss, which they denote CoVaR, using quantile regressions on asset returns computed using data on market equity and book value of the debt. Hartmann et al. (2005) use multivariate extreme value theory to estimate the systemic risk in the U.S. and European banking systems. Similarly, de Jonghe (2009) presents estimates of tail betas for European financial firms as their systemic risk measure. Huang, Zhou and Zhu (2009) use data on credit default swaps (CDS) of financial firms and time-varying stock return correlations across these firms to estimate expected credit losses above a given share of the financial sector's total liabilities. Goodhart and Segoviano (2009) look at how individual firms contribute to the potential distress of the system by using the CDSs of these firms within a multivariate copula setting.

Therefore, MES is not the only systemic risk measures currently proposed. Among others, there is the CoVaR, tail betas and measures based on credit default swaps. However, the MES, in comparison with other measures of firm-level risk have shown a higher predictive power in detecting a bank's contribution to a crisis (Acharya et al. 2010).

3. Estimation framework, data and variables

In this section, first we describe our regression framework, then we examine the sample and the data, and finally we focus on the explanation of the key independent variables (securitization and previous securitization), the dependent variables (changes in banks systemic risks) and the control variables.

3.1 Estimation framework

We design an empirical framework to investigate whether the market views asset securitization as increasing or reducing a bank's risk profile, by regressing changes in banks systemic risk on a securitization dummy, a previous securitization dummy and on a set of control variables.

First, we employ two different measures of systemic risk: the marginal expected shortfall (MES) and the expected shortfall (ES).

Second, for each risk measure, we estimate two baseline equations: model 1 and model 2.

Model 1:

$$\begin{aligned} y_{it} &= \alpha + \beta_1 \sec_{1it} + \beta_2 prev\_\sec_{2it} + \beta_3 loans_{3i(t-1)} + \beta_4 equity\_ratio_{4,i(t-1)} + \\ &+ \beta_5 size_{5,i(t-1)} + \beta_6 imp_{6,i(t-1)} + \beta_7 liquidity_{7,i(t-1)} + \beta_8 tier1\_ratio_{8,i(t-1)} + \beta_9 roae_{9,i(t-1)}) \qquad (3) \end{aligned}$$

where y_{it} is our dependent variable (i.e.MES and ES), *sec* and *prev_sec* are the key independent dummy variables; the other regressors, all lagged one year, are bank specific variables, selected from banks balance sheet and off-balance sheet items. These control variables will be describe in section 3.3. Following Wu et al. (2010) and Berger et al. (2010), to address a potential endogeneity concern in our analysis, recognizing that this may not be sufficient, we use lagged control variables (i.e. bank-specific attributes from the previous period but dummy variables from the current period). As variables from the previous period can be viewed as predetermined, this approach lets us circumvent the endogenous variables problem. Moreover, using bank-specific attributes from the previous period can also be justified assuming there is a time lag for bank-specific variables to affect a bank's equity return.

To control for potential cycle effects, common to all banks but varying over the analyzed period, we include time effects that we omit in equation (1) for ease of exposition.

To test whether a structural change occurs in the relationship between the securitization and the banks' risk exposure over the period 2007-2009, we estimate a second model, where we include an interaction variable between the securitization and the dummy CRISIS that takes the value of 1 during the years 2007-2009 and zero in the previous ones (2000-2006). In particular, for each dependent variable, we rerun the following regression[1]:

Model 2:

$$y_{it} = \alpha(+\beta_1 \sec_{1it} * crisis + \beta_2 prev\_\sec_{2it} + \beta_3 loans_{3i(t-1)} + \beta_4 equity\_ratio_{4,i(t-1)} + \\ + \beta_5 size_{5,i(t-1)} + \beta_6 imp_{6,i(t-1)} + \beta_7 liquidity_{7,i(t-1)} + \beta_8 tier1\_ratio_{8,i(t-1)} + \beta_9 roae_{9,i(t-1)}) \qquad (4)$$

We specify that the statistical analysis of the daily stock prices' time series reveals the presence of a structural break in year 2007. We investigate the presence of that break through the implementation of one of the methods ad hoc used. Generally, these techniques test the presence of changes in the regressions' coefficients through the use of the F statistic. We decide to employ the Chow test[2], which tests the null hypothesis of breaks' lack. The value of F statistic allows us to reject the null hypothesis of breaks' lacks for both models with a significant level lower than 1%.

Third, following the empirical analysis of Wu et al. (2010), we estimate models 1 and 2 in two stages. In the first stage, we ignore the panel data structure and apply simple ordinary least squares (OLS) for the estimation. In the second stage, recognizing the panel structure of our data, we incorporate fixed effects/random effect in our estimations. To decide whether the FE or RE model would be more appropriate, the Hausman test[3] is carried out. Under the null hypothesis, both models are consistent when their estimates do not differ significantly. When this difference is statistically significant (low p-value), we should reject the RE model as inconsistent. The empirical verification strategy would be, therefore, as follows. First, we estimate the FE models, then we estimate the RE model in order to employ the Hausman test. The indications of the latter test enable us to draw the final conclusions. In our analysis, this difference is not statistically significant. Therefore, we will base our conclusions on the RE model results.

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[1] Also in equation (6) we control for time effects that we omit for ease of exposition.

[2] Chow G., 1960, "Tests of equality between sets of coefficients in two linear regressions", *Econometrica* 28 (3).

[3] Hausman, J.A. "Specification Tests in Econometrics", Econometrica, 46(6), 1251-71, 1978.

3.2 Sample and data

To test the relationship between securitization and banks' risk, we first need to select all the banks having placed at least one cash securitization[4] during the period under investigation (2000-2009), from banks that did not. To this end, we collect data from the Talete Creative Finance[5] database, providing information on all the cash securitizations carried out from 1999 onwards. From this database, we draw a list of deals solely originated from banks.

We mostly employ micro-data from banks' financial statements (balance sheets and income statements) and the measure of capital for regulatory purposes. All these data are drawn from the Bankscope-Bureau van Djik database. Our sample includes all commercial banks with headquarters (including the registered office) in Italy for which the data needed to estimate the econometric model were available. More precisely, our sample banks are all the intermediaries present in the supervisory register of the Bank of Italy (according to the article No. 106 of TUB, the Italian Banking Law) and classified as commercial banks or savings banks. Cooperative credit banks (BCCs) are not included in the sample because of their special nature. In fact, cooperative banks behaviour is special in terms of both activity and size and a comparative analysis between them and the other banks would incur the risk of providing biased results. Furthermore, in Italy these banks do not engage in securitization as a single originator; rather, they participate in multi-originator transactions. Presumably, this choice depends on the fact that smaller institutions tend to benefit from jointly pooling assets; for example, they may obtain a better rating because of the added diversification (Martin-Oliver and Saurina, 2007).

It should be noted that, due to the lack of values in different years for the different variables, the final sample is composed of 83 securitizations undertaken by 21 listed banks over the period 2000-2009.

Table 1

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[4] We do not study synthetic securitization because, during the period under consideration, the number of synthetic deals was rather limited among Italian banks. Notwithstanding, we do not exclude that future research could adopt our analysis framework also to study the synthetic securitization focusing on the effects on banks risk. Furthermore, we do not consider on-balance-sheet securitizations, i.e., covered bonds, because they were not employed in Italy during the analysed period.

[5] Talete Creative Finance is an independent advisor for the analysis and structuring of securitizations. This company is also the editor of the 'Securitization.it' website, where it is possible to obtain the data used in this paper.

Table 1 shows descriptive statistics for the Italian securitization market as a whole (listed and not-listed banks); Since its introduction in the Italian system in 1999 with Law No. 130, securitization has spread rapidly. The deal numbers per year increased rapidly in the early 2000s, reaching a peak in 2001 with 59 transactions placed. From 2001 to 2006, the number of average transactions per year was 43. In 2007, the deal numbers dropped. Since 2001, the issuance volumes have consistently been significant and have never fallen below the threshold of 30 billion euros; even in 2007 that is a special year. We notice that following the peak in 2005 (41 billion euros), it is possible to envisage a trend towards lower issuance volumes.

3.3 Variables

Key independent variables: securitization dummy and previous securitization dummy

To capture the securitization activity placed by the Italian banks during the analyzed period, in models (1) and (2) we consider two different securitization dummy variables. First, we include a securitization dummy (SEC), coded 1 if the specific bank securitizes in a given year and 0 otherwise.

Then, to account for the securitizations undertaken by a bank in the previous years, we include another securitization regressor (PREV_SEC), coded 1 if the bank *i* placed at least one securitization in the period before the considered year and 0 otherwise. We decide to add this variable because a consolidated expertise may represent an incentive to use the securitization channel once again (Agostino and Mazzuca, 2011).

Dependent variables: tail and systemic risks

The dependent variables are the changes in banks' risk profile. For ease of exposition, however, we discuss these variables below in levels.

In order to investigate the impact of securitization on the originator banks' incentive towards risk, which could have significant financial stability implication, we adopt two measures of risk using the Expected Shortfall (ES) and the Marginal Expected Shortfall (MES) as developed by Acharya et al. (2010).

Since the Expected Shortfall (ES) is the expected loss conditional on the loss being greater than the VaR, we estimate it as follows:

$$ES_\alpha = -E\left[R \middle| R \leq -Var_\alpha\right] \quad (5)$$

where we consider α = 5%.

We focus on ES because it is coherent and more robust than VaR as largely investigated by the literature on the topic. Moreover, since we investigate the effect of securitization on bank's risk exposure pre and post the 2007 crisis, we know that VaR models do not work under market stress. VaR models are usually based on normal asset returns and do not work under extreme price fluctuations. The estimation methods used for standard VaR models have problems for measuring extreme price movements. They assume that the asset returns follow a normal distribution and disregard the fat-tailed properties of actual returns, underestimating the likelihood of extreme price movements. On the other hand, the concept of VaR as a risk measure has problems for measuring extreme price movements. By definition, VaR only measures the distribution quantile and disregards extreme loss beyond the VaR level. Thus, VaR may ignore important information regarding the tails of the underlying distributions. This means it fails to take into account the so called "tail risk". To alleviate the problems inherent in VaR, Artzner et al (1997, 1999) propose the use of Expected Shortfall. Expected shortfall is the conditional expectation of loss given that the loss is beyond the VaR level. Thus, by definition, expected shortfall considers losses beyond the VaR level. Yamai and Yoshiba (2002) show that expected shortfall has no tail risk under more lenient conditions than VaR.

Starting from the same measure, the Expected Shortfall, but computing it for the overall banking system, Acharya et al. (2010) and Brownlees et Engle (2010) derive the Marginal Expected Shortfall of bank *i* as the derivative of the market Expected Shortfall with respect to bank *i* weight in the market index and ultimately define MES as:

$$\frac{\partial ES_\alpha}{\partial y_i} = -E(r_i | R \leq VaR_\alpha) \equiv MES_\alpha^i \quad (6)$$

In Table 3, when we consider the 5% winsorization, the R-square is 0.1410 in model 1 and 0.1216 in model 2; it becomes higher if we turn to 10% winsorization. In the estimates of Model 1 for the ES, we find a positive and significant coefficient for the dummy *sec* and for the dummy *prev_sec* at 5% and 10%, respectively. Therefore, the ES increases with current securitization and even more if the bank were involved in this activity also in the previous years. This may suggest that securitizing banks have, on average, higher expected losses in case of extreme events. This adds new evidence on the main findings in the literature that focused on the evidence that risk transfer through securitization is relatively insignificant compared to the risk retained by the originating bank. We show that this risk retention is in terms of an increase of Expected Shortfall.

Among the control variables, we have a significant and positive coefficient for the *size* variable, allowing us to control for potential size effect, that is to say, the possibility that larger banks tend to have higher risk exposure and at the same time, that larger banks are more likely to securitize than smaller banks (Uzun and Webb, 2007).

In Table 4, when we consider the 5% winsorization, the R-square is 0.2208 in model 1 and 0.1907 in model 2; it becomes higher if we turn to 10% winsorization. The estimation of Model 1 with MES as dependent variable allows us to investigate whether this increase in the tail risk through securitization is also correlated with the market, originating systemic risk. The coefficients for the dummy *sec* and for the dummy *prev_sec* are significant at 5% and 10%, respectively, confirming that the tail risk induced by the securitization is highly correlated with the market. Securitizing banks are likely to contribute more in case of systemic crisis than other banks. More interestingly, we find a negative and significant coefficient for the size and equity ratio, which can be considered as a rough proxy for leverage ratio. This is consistent with the evidence of Brownless and Engle (2010) that MES is an increasing function of market size and financial leverage

The estimation of the model 2, both with ES and MES, allows us to investigate whether the evidences we had in the results discussed above (referred to the overall period 2000-2009), differs if we take into account the 2007 financial crisis. In other words, in Model 2 we investigated whether the financial crisis led to a reduction in the tail risk of the securitization activity, somehow disciplining the managers of the originating banks towards a higher awareness of the implied risk associated with these risk transfer activities, or to an increase due to higher difficulties to manage risks in bad financial market conditions. Surprisingly, we do not find such evidences. We find that the coefficient of the interaction variable *Int_sec_crisis* is positive, but insignificant for both the ES and the MES. Since the financial crisis illustrated how securitization activity of the years before 2007 had negative implication for financial stability, this result suggests that the potential consequences of the securitization in terms of systemic risk are still there.

Table 5

Table 6

To account for heterogeneity across banks, we also estimate a panel random-effects model. Results are reported in Table 5 for ES and in Table 6 for MES. All the results are consistent with the OLS estimations.

In particular, referring to the key independent variables of Table 5, the estimates of model 1 with ES as dependent variable show a high positive significance of both the securitization dummies, when winsorising at 5% and at 10%. The results of model 2 confirm the empirical evidence of Table 3, in which we find that the coefficient of the interaction variable *Int_sec_crisis* is positive but insignificant.

If we turn to consider the random effects estimations referring to MES, the *sec* and *pre_sec* of model 1 are again positive and significant, with the only exception of the *prev_sec* variable which loses significance when winsorising at 10%.

Table 6 reports the random effects estimates of MES. These results confirm the findings obtained with the OLS regressions. In detail, referring to model 1, the key independent variables are positive and significant, but they lose significance in model 2, where both the coefficients of the *Int_sec_crisis* and of the *prev_sec* are positive and insignificant.

Finally, the positive significant sign of the size control variable suggests that the dimension is also relevant in determining the banks' risk-taking and the banks' decision of securitizing. Indeed, since the structuring of securitization deals implies high fixed costs, it is more plausible that larger banks are better at bearing them. Moreover, it is supposed that larger banks are better able to develop the expertise necessary to securitize and, most of all, to constitute a pool of assets with sufficient volume to originate securitization transactions in an efficient way. Moreover, it is assumed that larger banks have a strong distribution capacity as well as important business relationships and/or greater bargaining power with potential investors, thus contributing to an easier placement of the structured finance securities on the market.

where r_i is the return of the bank i, $\alpha = 5\%$ and MES^i_α is bank i 's marginal expected shortfall, measuring how bank i 's risk taking adds to the bank's overall risk. In other words, MES can be measured by estimating group i 's losses when the market is doing poorly.

The main rationale behind the MES with respect to the standard measures of firm-level risk, such as VaR, expected loss, or volatility, is that they have almost no explanatory power, while beta has only a modest explanatory power in detecting systemically risky banks. We recall that the difference between MES and beta arises from the fact that systemic risk is based on tail dependence rather than on average covariance so that it better fits the definition of systemic risk in terms of expected losses of each financial institution in a future systemic event in which the overall financial system is experiencing losses.

Moreover, the great advantage of MES is given by the possibility of linking the market return dynamic properties to single equity returns behaviour, possibly using bivariate models, and without the need of large system estimation compared to other measures of systemic risk (see section 2).

Control variables

Since the banks' risk profile could be affected by factors different than securitization, we include a set of control variables in model 1 and model 2.

All of the control variables (except for dummy variables) are measured in changes. For ease of exposition, we discuss these variables below in levels.

To control for specific bank characteristics, we include variables that might explain differences in the bank's risk taking. In detail, we consider the following accounting-based variables: the loans ratio (total loans/total assets, LOANS), the equity ratio (equity/total assets %, EQUITY_RATIO), the total assets (natural log of total assets, SIZE), the impaired loan ratio (impaired loans/gross loans, IMP), the liquidity ratio (liquid assets/customer and short term funding, LIQUID), the return on equity (net income/total equity, ROE), the Tier1 ratio (TIER1).

4. Empirical analysis and results

Table 2 summarizes some relevant statistical information for the key independent variables, for the dependent variables, and for the control variables. While the regressions are run in changes, we report means of levels and changes for all the variables.

Table 2

Because many of our variables have large positive and negative outliers, to prevent extreme values from biasing the results of our study, without losing observations, we winsorise them at 5%[6] .

[6] For other contributions that adopt the same method, see Barth et al. (2006), Muiño Vázquez and Trombetta (2009).

Winsorising at 5% involves assigning to outliers beyond the 5th and 95th percentiles a value equal to the value of the 5^{th} or 95^{th} percentile in order to limit the influence of outliers on the regression. To make sure that the results do not depend on the specific treatment of the outliers, in our Tables, we report the estimates obtained when winsorising at 5% and 10%.

In all cases, the observations are clustered at the bank level. In fact, because in our sample the same bank may be present in different years, it seems appropriate to allow the errors to be correlated for the same intermediary over time. Moreover, by doing so, we obtain standard errors robust to heteroscedasticity.

Table 3

Table 4

Table 3 and Table 4 present estimation results of OLS regressions for Model 1 (Panel A) and for Model 2 (Panel B), having the ES and MES as dependent variables, respectively. The robust standard errors are reported in column 3.

5. Further analysis

To further verify our results, we implement a robustness check concerning the estimation method, by using an ordered probit model.

Since our aim is to model the probability of a securitizing bank to become "systemically" riskier during the analysed period on a number of factors, we choose to apply a probit model (Altunbas et al., 2010). In particular, following Berger et al. (2010), we adopt an ordered model because the employing of an ordinal dependent variable allows us to analyse the behaviour of the bank *i*, in terms of probability, distinguishing between changes in bank behaviour and relatively constant behaviour[7]. Moreover, we focus on changes (cut-off) of 40%[8]. In particular, our dependent variables take on the following values:

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[7] Differently from Berger et al. (2010), we adopt an ordered probit model instead of a logit one. This because our dependent variable can be considered as a synthesis of a latent continuous variable. As a robustness check, we also run a logit model and we find consistent results.

[8] We specify that ,in the robustness test, we use alternative cut-offs. All results are available upon request.

a. 1 if the bank experienced a drop in risk-taking (relative to the previous year) of more than 40% (DECR);
b. 2 if the banks' risk- taking moved within a range of +/- 40% (CONST);
c. 3 if the banks' risk-taking increased by more than 40% (INCR).

We adopt the following ordered probit model:

$$\Pr(y_{it} = j) = \Phi(\beta X'_{i,t} + \gamma ctrl_{i,t-1}) \,, \qquad j = 1,2,3 \quad (7)$$

where the ordered outcomes are modelled to arise sequentially as the latent variable, y^*, crosses progressively higher thresholds[9]. In detail, y_{it} = 1, 2 or 3 depending on whether the change in risk-taking of bank *i* at time *t* respectively decreases, remains within a definite range or increases; *Pr* is the probability, Φ is the standard cumulative normal probability distribution, $X_{i,t}$ is the vector of securitization (dummy) variables and $ctrl_{i,t-1}$ is the vector of the control variables (all described in subsection 3.3); as usual, β and γ parameters are estimated by maximum likelihood.

In the ordered probit model the sign of the regression parameters, β, can be immediately interpreted as determining whether the latent variable, y^*, increases with the regressor. If β_j is positive, then an increase in x_{ij} necessarily decreases the probability of being in the lowest category (y_i =1) and increases the probability of being in the highest category (y_i =3). So, for example, a positive coefficient for the securitization dummy or the previous securitization dummy indicates that an increase of these variable corresponds to an increase of the probability for the bank of belonging to the upper risk-taking category, i.e. greater than 40%. On the opposite, a negative coefficient indicates that an increase of the securitization variable determines a decrease in the probability for bank *i* to belong to the higher risk-taking class. So, we rerun all calculation by using the ordered probit model (7), both for ES and MES, but our results remain qualitatively unchanged, suggesting that our findings are not driven by the modelling technique we chose.

Table 7

[9] We decide to adopt an ordered probit model because our dependent variables can be considered as a synthesis of a latent continuous variable.

Table 7 summarizes the estimates for the MES. Since the ES probit results are very similar to the MES ones, for ease of exposition we do no present the findings referring to this risk measure, but all estimations and Tables are available upon request.

6. Conclusions

Our research on the relationships between asset securitization and risk measures as the expected shortfall and the marginal expected shortfall yields a number of interesting findings. First, our results suggest that securitizing banks have, on average, higher expected losses in case of extreme events. This add new evidence on the main finding in the literature, that show evidence that the risk transfer activity through securitization is relatively insignificant compared to the risk retained by the originator bank, by showing this risk retention implies an increase of tail risk. Second, we find that the relation between securitization and ES was unaffected by the financial turmoil started in 2007. Moreover, we notice that the originator banks experienced higher systemic risk (MES), both in pre and after 2007- crisis, confirming the opportunity for new rules on the securitization markets aiming to overcome the negative implication for the financial stability of these operations.

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Table 1. The Italian securitization market over the period 2000–2007: deal numbers and issuance volumes

Year	Deal numbers	Issuance volume (millions of euros)	Issuance volumes per deal
2000	25	12.086	483.44
2001	59	33.967	575.71
2002	41	30.606	746.49
2003	40	30.141	753.53
2004	39	35.028	898.15
2005	40	40.804	1020.1
2006	39	35.707	915.56
2007	29	33.919	1169.62
2008	30	n.a	n.a
2009	26	n.a	n.a

Source: Securitization.it.

Table 2. Summary statistics for the dependent, the key independent and the control variables

	Variable	Obs.	Mean of level	Mean of change
Dependent variables	ES	166	0.00388656	0.095350135
	MES	166	-0.041979	-0.6065153
Key independent variables	Sec	210	0.3428571	n.a.
	Prev_sec	210	0.7238095	n.a.
Control variables	Loans	201	0.3422239	0.0925363
	Equity_ratio	185	0.0741959	0.0345064
	Size	203	6.931395	0.0068586
	Imp_loans	183	1.752285	0.5554443
	Tier1	180	5.9345976	0.0488155
	Roe	202	0.3700048	-0.3143841
	Liquidity	177	13.122176	0.1145027

Notes: Sec is a dummy coded 1 if a bank places at least one securitization in a year, zero otherwise; Prev_sec is a dummy coded 1 if a bank places at least one securitization in the period before the analyzed year, zero otherwise; Size is measured as ln of total assets; the other variables are described in Section 3.3. Continuous variables are winsorised at 5%. While regressions are run in changes, we report means of levels and changes of the variables.

Table 3. Model 1 and model 2: OLS estimates of ES

OLS regressions - Dependent variable ES	Panel A: Model 1						Panel B: Model 2					
	winsorization 5%			winsorization 10%			winsorization 5%			winsorization 10%		
	Coefficients (1)	Sig (2)	Robust standard errors (3)	Coefficients (1)	Sig (2)	Robust standard errors (3)	Coefficients (1)	Sig (2)	Robust standard errors (3)	Coefficients (1)	Sig (2)	Robust standard errors (3)
Key independent variables												
Sec	0.17210	**	0.07204	0.13817	**	0.05453						
Int_sec_crisis							0.20209		0.12357	0.13744		0.10230
Prev_sec	0.38248	***	0.19528	0.13106	**	0.05810	0.12116	*	0.06861	0.09316		0.06849
Control variables												
Loans	0.04574		0.27063	0.15380		0.36045	0.02534		0.26561	0.13504		0.38242
Equity_ratio	-0.43366	**	0.16820	-0.53802	***	0.16749	-0.36163	**	0.15682	-0.48582	***	0.16039
Size	12.73046	**	5.00037	14.60651	***	4.81031	11.45939	**	5.68340	13.49194	**	5.46517
Liquidity	-0.04901		0.13655	-0.01504		0.18036	-0.04738		0.14045	-0.00869		0.18691
Imp_loans	-0.01944		0.04514	-0.00023		0.08109	-0.02032		0.03987	-0.01180		0.07239
Tier1	-0.27264	*	0.15021	-0.39714	**	0.14415	-0.29239	*	0.17394	-0.42256	**	0.17748
Roe	-0.01626		0.05726	-0.02212		0.06539	-0.03273		0.05817	-0.04220		0.06628
cons	-0.21536	***	0.07156	-0.21360	***	0.06651	-0.12228	*	0.06698	-0.13958	*	0.06813
R- Square	0.14100			0.15510			0.12160			0.13070		
Adj. R-Square												
Root MSE	0.37908			0.31174			0.38335			0.31621		
Number of banks (clusters)	21			21			21			21		

Dependent variable - Panels A and B: changes in ES

Notes: (a) we estimate OLS regressions for changes in ES. In Panel A we run the model 1 (explanatory variables: sec, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe), while in Panel B we run the model 2 (int_sec_crisis, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe); (b) all the control variables are lagged 1 year; (c) all the explanatory variables (except the dummy variables) are measured in changes; (d) columns 3 of Panel A and Panel B report robust standard errors; (e) in Panel A and Panel B all the variables (except the dummy variables) are respectively winsorized at 5% and 10%. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Table 4. Model 1 and model 2: OLS estimates of MES

OLS regressions - Dependent variable MES	Panel A: Model 1						Panel B: Model 2					
	winsorization 5%			winsorization 10%			winsorization 5%			winsorization 10%		
	Coefficients (1)	Sig (2)	Robust standard errors (3)	Coefficients (1)	Sig (2)	Robust standard errors (3)	Coefficients (1)	Sig (2)	Robust standard errors (3)	Coefficients (1)	Sig (2)	Robust standard errors (3)
Key independent variables												
Sec	0.45029	**	0.21454	0.30916	**	0.15566						
Int_sec_crisis							0.38180		0.36744	0.29130		0.27189
Prev_sec	0.38248	*	0.19528	0.25187	*	0.15196	0.26039		0.18532	0.16914		0.15887
Control variables												
Loans	1.25976	*	0.62194	1.45972		0.88118	1.19857	**	0.61427	1.42173		0.93796
Equity_ratio	-1.94043	**	0.72291	-1.97909	***	0.57640	-1.77816	***	0.71031	-1.86449	***	0.56487
Size	38.51958	***	9.54211	36.93581	***	10.87047	34.83305	***	10.59394	34.38691	***	11.92290
Liquidity	-0.37814	*	0.33104	-0.26279		0.32044	-0.40838		0.35894	-0.25363		0.34352
Imp_loans	0.17516	*	0.12616	0.27874		0.17600	0.17045		0.11709	0.25277		0.17125
Tier1	-0.56417		0.42171	-0.83540	**	0.39659	-0.57980		0.45486	-0.88530	*	0.45490
Roe	0.04974		0.14323	0.03115		0.14790	0.01740		0.15309	-0.01190		0.14822
cons	-0.68622	***	0.21255	-0.54969	***	0.19164	-0.44469	**	0.18993	-0.38438	*	0.20415
R- Square	0.2208			0.2086			0.1907			0.1871		
Adj. R-Square												
Root MSE	0.93439			0.74116			0.95229			0.75113		
Number of banks (clusters)	21			21			21			21		

Dependent variable - Panels A and B: changes in MES

Notes: (a) we estimate OLS regressions for changes in MES. In Panel A we run the model 1 (explanatory variables: sec, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe), while in Panel B we run the model 2 (int_sec_crisis, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe); (b) all the control variables are lagged 1 year; (c) all the explanatory variables (except the dummy variables) are measured in changes; (d) columns 3 of Panel A and Panel B report robust standard errors; (e) in Panel A and Panel B all the variables (except the dummy variables) are respectively winsorized at 5% and 10%. * Significant at 10%. ** Significant at 5%. *** Significant at 1%

Table 5. Model 1 and model 2: Random effects (RE) - GLS estimates of ES

Random-effects GLS regressions - Dependent variable ES	Panel A: Model 1						Panel B: Model 2					
	winsorization 5%			winsorization 10%			winsorization 5%			winsorization 10%		
	Coefficients (1)	Sig (2)	Robust standard errors (3)	Coefficients (1)	Sig (2)	Robust standard errors (3)	Coefficients (1)	Sig (2)	Robust standard errors (3)	Coefficients (1)	Sig (2)	Robust standard errors (3)
Key independent variables												
Sec	0.17210	**	0.08234	0.13817	**	0.06537						
Int_sec_crisis							0.20214		0.15872	0.13721		0.11917
Prev_sec	0.17545	*	0.09697	0.13106	*	0.08307	0.11866		0.09775	0.08409		0.08804
Control variables												
Loans	0.04574		0.34464	0.15380		0.45114	0.02721	*	0.34172	0.14268	*	0.45234
Equity_ratio	-0.43366	*	0.24742	-0.53802	**	0.23964	-0.36116	**	0.25253	-0.48012	**	0.24603
Size	12.73046	**	5.50306	14.60651	***	5.57944	11.61963		5.68343	14.16877		5.70915
Liquidity	-0.04901		0.12813	-0.01504		0.15209	-0.04684		0.12356	-0.00286		0.15242
Imp_loans	-0.01944		0.05214	-0.00023		0.87990	-0.02015		0.05157	-0.01301		0.08748
Tier1	-0.27264		0.18143	-0.39714	**	0.18466	-0.28976		0.18667	-0.41261	**	0.19272
Roe	-0.01626		0.05769	-0.02212		0.72413	-0.03254		0.55001	-0.04161		0.07035
cons	-0.21536	**	0.10027	-0.21360	**	0.08975	-0.12109	*	0.09401	-0.13528	*	0.08881
R- Square (overall)	0.1410			0.1551			0.1215			0.1302		
Adj. R-Square												
Wald χ2 test	17.17			23.85			12.99			18.98		
Number of banks (clusters)	21			21			21			21		

Dependent variable - Panels A and B: changes in ES

Notes: (a) we estimate random effects (RE) - GLS regressions for changes in ES. In Panel A we run the model 1 (explanatory variables: sec, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe), while in Panel B we run the model 2 (int_sec_crisis, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe); (b) all the control variables are lagged 1 year; (c) all the explanatory variables (except the dummy variables) are measured in changes; (d) columns 3 of Panel A and Panel B report robust standard errors; (e) in Panel A and Panel B all the variables (except the dummy variables) are respectively winsorized at 5% and 10%; (f) time effects are included in all estimates. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Table 6. Model 1 and model 2: Random effects (RE) - GLS estimates of MES

Random-effects GLS regressions - Dependent variable MES	Panel A: Model 1						Panel B: Model 2					
	winsorization 5%			**winsorization 10%**			**winsorization 5%**			**winsorization 10%**		
	Coefficients (1)	**Sig (2)**	**Robust standard errors (3)**	**Coefficients (1)**	**Sig (2)**	**Robust standard errors (3)**	**Coefficients (1)**	**Sig (2)**	**Robust standard errors (3)**	**Coefficients (1)**	**Sig (2)**	**Robust standard errors (3)**
Key independent variables												
Sec	0.45029	**	0.20952	0.30916	**	0.15366						
Int_sec_crisis							0.38180		0.37597	0.29130		0.27189
Prev_sec	0.38248	*	0.22305	0.25187		0.18643	0.26039		0.22874	0.16914		0.15887
Control variables												
Loans	1.25976	*	0.75848	1.45972	*	1.01359	1.19857	*	0.75780	1.42173	*	0.93796
Equity_ratio	-1.94043	***	0.72164	-1.97909	***	0.64955	-1.77816	**	0.72274	-1.86449	***	0.56487
Size	38.51958	***	12.49752	36.93581	***	12.54339	34.83305	***	12.23145	34.38691	***	11.92290
Liquidity	-0.37814		0.37604	-0.26279		0.37061	-0.40838		0.39064	-0.25363		0.34352
Imp_loans	0.17516		0.14577	0.27874		0.21374	0.17045		0.14664	0.25277		0.17125
Tier1	-0.56417		0.48350	-0.83540	*	0.46466	-0.57980		0.47015	-0.88530	*	0.45490
Roe	0.04974		0.16717	0.03115		0.17629	0.01740		0.17143	-0.01190		0.14822
cons	-0.68622	***	0.25490	-0.54969	**	0.21536	-0.44469	*	0.23190	-0.38438	*	0.20415
R- Square (overall)	0.2288			0.2086			0.1907			0.1871		
Adj. R-Square												
Wald χ2 test	29.24			31.74			27.08			18.98		
Number of banks (clusters)	21			21			21			21		

Dependent variable - Panels A and B: changes in MES

Notes: (a) we estimate random effects (RE) - GLS regressions for changes in MES. In Panel A we run the model 1 (explanatory variables: sec, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe), while in Panel B we run the model 2 (int_sec_crisis, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe); (b) all the control variables are lagged 1 year; (c) all the explanatory variables (except the dummy variables) are measured in changes; (d) columns 3 of Panel A and Panel B report robust standard errors; (e) in Panel A and Panel B all the variables (except the dummy variables) are respectively winsorized at 5% and 10%; (f) time effects are included in all estimates. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Table 7. Model 1 and model 2: Ordered probit models focusing on MES changes of 40%

Dependent variable MES: Pr ($riskier_i$=3)	Panel A: Model 1				Panel B: Model 2			
	Coefficients (1)	Sig (2)	Robust standard errors (3)	Marg. effects (4)	Coefficients (1)	Sig (2)	Robust standard errors (3)	Marg. effects (4)
Key independent variables								
Sec	0.4837307	**	0.2145443	0.1643511				
Int_sec_crisis					0.1598064		0.4161426	0.0548216
Prev_sec	0.1582578		0.3049763	0.0501183	0.0195394		0.3596745	0.0064455
Control variables								
Loans	0.3652774	***	0.1184184	0.1194214	0.3634363	***	0.0855087	0.1203234
Equity_ratio	-1.2395	**	0.3555952	-0.405234	-1.14161	**	0.5736283	-0.3779547
Size	18.11523	***	7.783002	8.191812	15.83109	***	6.790291	8.551939
Liquidity	-0.4062286	*	0.3049763	-0.13281	-0.4089718	***	0.2239516	-0.1353989
Imp_loans	0.0521382	*	0.0541187	0.0170457	0.0514672	*	0.0499545	0.0170393
Tier1	0.103832		0.148239	0.0339461	0.0579279		0.1830783	0.0191783
Roe	0.0123274		0.0162013	0.0040302	0.0120371		0.0180055	0.0039851
Number of obs,	111				111			
Log pseudolikelihood	-106.36065				-108.22225			
Number of banks (clusters)	21				21			
Prob>chi^2	0				0			
Pseudo R^2	0.1092				0.0936			

Dependent variable - Panels A and B: changes in MES (Δ MES) of 40%.
Notes: (a) we estimate ordered probit models for changes in MES of 40%. In Panel A we run the model 1 (explanatory variables: sec, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe), while in Panel B we run the model 2 (int_sec_crisis, prev_sec, loans, equity ratio, size, liquidity, imp_loans, tier1 and roe). The dependent variable takes on the value 1 if there was a drop in MES of at least 40% relative to the previous year, it takes on the value 2 if MES remained within the interval +/- 40%, and it takes on the value 3 if there was an increase in MES of more than 40%; (b) all the control variables are lagged 1 year; (c) all the explanatory variables (except the dummy variables) are measured in changes; (d) columns 3 of Panel A and Panel B report robust standard errors; (e) columns 4 of Panel A and Panel B present the marginal effects referring to the outcome 3, that is the upper MES category (changes > 40%); (f) time effects are included in all estimations. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.