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Securitization and Crash Risk: Evidence from Large European Banks.

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Securitization and Crash Risk: Evidence from Large European Banks.

Abstract

The 2008 global financial crisis highlights the importance of securitization and crash risk. Yet there is a dearth of papers exploring the link between securitization and crash risk. We analyze 7,096 securitization deals made by large European listed banks between 2000 and 2017. Our paper provides evidence that bank risk declines in the year of the securitization and increases in the following year. We also show that this effect is driven by low-risk securitization deals. We use a dynamic panel data approach to establish a causal relationship and control the robustness of our results by using different tail risk measures (such as crash risk, value at risk, and expected shortfall). We also show that the risk reduction effect is weaker in crisis periods relative to normal times. Our findings have policy implications as regulators attempt to revive European securitization markets.

Keywords: securitization; crash risk; tail risk; European banks; financial crisis

JEL Codes: F30; G01; G14; G21; G32

Securitization and Crash Risk: Evidence from Large European Banks

"Securitisation markets are a key funding channel for the economy, increasing the availability and reducing the cost of funding for households and companies by opening up investment opportunities to a wider investor base, diversifying risk across the economy and freeing up bank balance sheets to lend."

Commissioner Jonathan Hill, Eurofi Financial Forum, September 2015.

1. Introduction

Securitization[1] is credited as both a catalyst and solution to the 2008 global financial crisis (hereafter denoted as GFC). Prior to the GFC, securitization was a popular method of financing the mortgage and consumer credit markets.[2] The technique came to be regarded as one of the biggest financial innovations of the last century (McConnell and Buser, 2011; FCIC Report, 2011; Gorton and Metrick, 2012 and Buchanan, 2016). However, a decade later, there is still a stigma surrounding the misuse of securitization prior to the GFC. Whilst many aspects of the US securitization market were decimated during the GFC, the European securitization market performed relatively well during and post-GFC[3].

Despite this, European securitization market volumes have declined substantially during the last decade and have struggled to recover. As Figures One and Figure Two indicate, there has been an anemic recovery in European securitization markets post-GFC. In the first half of 2018, there was more than €100 billion in placed issuances. However, the overall amount is still very low compared with pre-GFC levels, which approximated €450 billion (AFME, 2018).

[1] In this paper, we define securitization as a technique or process where a financial intermediary acquires financial assets (such as equity or debt instruments), repackages the cash flows on those equity or debt instruments, and issues marketable securities representing claims on the repackaged cash flows. This allows the original asset owners to remove the original items from their balance sheets and free it up for more lending (Culp and Neves, 1998; Cummins and Weiss, 2009). Basically, anything that is expected to bring in a steady stream of revenues can be securitized.
[2] Gorton (2012) estimates that 64% of US home mortgages and between 30 and 75% of US consumer loans were securitized prior to the GFC
[3] European residential MBS also performed well relative to covered bonds, sovereign and bank debt (AFME, 2018).

[INSERT FIGURE ONE ABOUT HERE]

[INSERT FIGURE TWO ABOUT HERE]

European securitization issuance has declined partly because of more intensive regulatory reforms[4] post-GFC which has curbed higher risk activities. For example, Capital Markets Regulation was the European implementation of the Basel III rules, and required issuers to keep 5 percent "*skin in the game*". As part of its quantitative easing measures, the European Central Bank bought asset backed securities. Over time, European regulators have taken a more supportive view towards securitization.[5] In 2015, the European Banking Authority called for lower capital charges on securitizations for certain qualifying deals. The European Commission placed securitization at the center of its plan for a Capital Markets Union and called to introduce more simple, transparent and standardized securitizations (or STS)[6,7]. As bank lending has become more constrained post-GFC, securitization has the potential boost credit and growth.

The recent GFC has also drawn increased attention to crash risk, which is a function of skewness. Crash risk is the risk of extreme negative values in the distribution of firm-specific returns, after adjusting for the return portions that co-move with common factors. Extreme negative events can impose significant losses on investors (Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2011a, b). Crash risk captures risk asymmetry and matters because large stock price declines can diminish firm value, investor wealth and potentially induce financial market instability. Consequently, investors will require higher expected returns for firms with more crash risk (Harvey and Siddique, 2000).

[4] Included in regulatory reforms is the fact that originators must retain part of the loan risk and banks and insurers must set aside more capital against such instruments.
[5] Regulating European securitizations after the crisis, Thomas Harde, FTimes. July 30, 2018.
[6] Regulating European securitizations after the crisis, Thomas Harde, FTimes. July 30, 2018.
[7] This new amended regulation will not appear until early 2019.

In this paper, we draw these literature streams together. Specifically, our paper answers the following research questions: Does securitization activity decrease the originators' risk? Does the relationship between securitization and risk differ for high and low-risk securitizations? We find a reduction in bank risk in the year a bank securitizes (a negative contemporaneous effect), but an increase in the following year (positive post-securitization effect). By distinguishing between high and low-risk deals, securitization transactions exhibit different effects on risk. In high-risk securitizations, banks may securitize opaque assets in anticipation of an increase in crash risk; in low-risk securitizations, our findings are very similar to results for the overall sample: there is evidence of a contemporaneous risk-reduction effect of securitization and a post-event increase in market risk. Finally, we also show that the risk reduction effect is weaker in the crisis period relative to normal times.

Existing research remains inclusive about the relationship between securitization and bank risk profile. Nor does the literature have a unique prediction about the direct effect of securitization on bank risk exposure (Casu et al., 2013; Michalak and Uhde, 2012; Hansel and Krahnen, 2007) and on bank ratings (Caporale et al., 2011). Different hypotheses about securitization and risk-taking primarily depends on how much risk is actually transferred to external investors. On one hand, the overall risk of originating banks is likely to decrease if the transferred tail risk of senior tranches exceeds the amount of default risk of the retained first-loss piece (Jiangli and Pritsker, 2008). On the other hand, most of the default risk typically remains within the banks' first-loss position, acting as a quality signal towards potential external investors (DeMarzo, 2005; Instefjord, 2005). Similarly, there are different expectations regarding the indirect effects of securitization on the banks' risk profile depending on the ex-post investment policies and by the way the banks' asset portfolios are restructured (Krahnen and Wilde, 2008).

Empirical identification of this relationship is challenging since the bank's decision to start a securitization deal is strictly endogenous (i.e., a bank decides if and when start a securitization deal and what are the underlying assets). There are also reverse causality (i.e., a bank starts a securitization deal based on its risk) and omitted variable issues to consider.

To overcome these challenges, we use an identification strategy based on a dynamic panel data model, which is consistent with recent literature (Fresard, 2010; Dessant et al., 2017; Gopalan et al., 2017) that enables us to address the reverse causality problem. Specifically, we include pre- and post-securitization treatment variables so that we can empirically test the reverse causality issue (i.e., whether a bank decides to start a securitization deal because it is more or less risky). Second, we deal with the omitted variables problem by using a panel data model with fixed effects at the bank level and year level, with standard errors clustered at the country level. Out results are robust to a variety of model specifications and various measures of crash and tail risk.

Our study contributes to the literature in several ways. First, our paper adds to the crash risk literature by examining the role and impact of securitization. The existing literature on stock price crash risk tends to focus on the effects of stock market characteristics on crashes (Chen et al., 2001; Hong and Stein, 2003; Huang and Wang, 2008). At the individual stock level information transparency is related to less crash risk. Managerial option incentives induce managerial opportunism such as hiding bad news, which is related to higher stock crash risk (Kim et al., 2011). We add to this literature by showing that securitization can affect bank-specific crash risk.

Second, we measure bank risk using the stock market tail risk of the originators. Various papers (e.g., Kara et al., 2016; Casu et al., 2013; Michalak and Uhde, 2012; Loutskina, 2011) use accounting information (as NPL, Z-score, etc): although these measures are available for both listed and non-listed banks, these measures are backward looking. A second group of papers (e.g., Iglesias-Casal et al., 2016; Battaglia et al., 2014, Nijiskens and Wagner, 2011; Battaglia and Gallo, 2013; Gorton and Metrick, 2012; Berger et al., 2015) use stock market returns to capture market risk (both in terms of systematic and systemic risks). Our decision to focus on stock market tail risk measures reflects the investors' asymmetric treatment of downside risk versus upside uncertainty (Caporale and Gil-Alana, 2012). The GFC has exacerbated the attention to extreme (negative) events, especially for banks, as outlined by Kosmidou et al. (2017). Different to Kosmidou et al. (2017) we focus on securitization, not on stock price. Consequently, we measure the effect produced by securitization deals on a large set of indicators of tail risk measures, concentrating on the probability of extreme negative events, i.e., crash risk.

Third, our paper focuses on European banking. Most securitization papers have focused on the U.S. (e.g., Casu et al., 2013; Loutskina and Strahan, 2009; Loutskina, 2011; Miam and Sufi, 2009; Chava and Purnanandam, 2011; Dell'Ariccia et al., 2012; Gorton and Metrick, 2012; Jiangli and Pritsker, 2008; Keys et al., 2010; Le et al., 2016; Wu et al., 2010; Trapp and Weiß, 2016); and there is only a handful of papers analyzing the link between securitization and risk in Europe (e.g., Kara et al., 2016; Michalak and Uhde, 2012; Farruggio and Uhde, 2015; Hansel and Krahnen, 2007; Franke and Krahnen, 2006).

Finally, our paper has important implications for policymakers as they try to revive European securitization markets. This is particularly relevant to Europe where securitization can be a vital funding tool and for SME borrowers to access the capital markets (AFME, 2018). To curtail crash risk, regulators should closely monitor banks' crash related risk taking and securitization behavior.

The remainder of the paper is organized as follows. In Section 2, we review the relevant literature and develop our research hypotheses. In Section 3, we describe our empirical methodology. The data and variables measurement are detailed in Section 4. In Section 5, we discuss the results, while Section 6 shows the robustness checks. Section 7 concludes.

2. Literature review and Hypothesis Development.

2.1 Securitization Literature Review

Securitization radically transformed the global financial landscape over the last couple of decades (Buchanan, 2016). It also came to be epitomized as a key trigger of the GFC. Once referred to as the "*alchemy*" by Lewis Ranieri at Salomon Brothers, securitization became the funding model and risk transfer method of choice for many global financial institutions over the last four decades. As a financing technique, securitization meets the needs of institutional investors like pension funds and insurance companies. Securitization can raise funding and support new lending to small and medium sized enterprises (SMEs), which is the dominant business unit in Europe.

The benefits of securitization are well documented (Kashyap and Stein (2000), Loutskina and Strahan (2007)). These benefits include: cheaper funding costs, credit risk diversification, freeing up equity for the financial institution, creation of new asset classes and the potential to accelerate earnings potential (Greenbaum and Thakor (1987), Schwarz (1991), Fabozzi (2005), Uzun and Webb (2007), Jiangli and Pritsker (2007), (Ashcraft and Schuermann, 2008)).

However, there are also potential drawbacks associated with the securitization process (Schwarz (1991), Morrison (2005), Parlour and Plantan (2008), Cerrato et al. (2012)). The rebundling process could lead to a lack of transparency and weakening of the due diligence process. Securitization may have potentially reduced incentives for lenders to carefully scrutinize and monitor borrowers due to the greater distance between the borrower and those who finally bear the default risk (Petersen and Rajan, 2002). Piskorski, Seru and Vig (2012) and Parlour and Plantan (2008) also tie a lack of ex-post monitoring incentives to securitization.

Although risk transfer is regarded as a benefit, understanding its consequences is less clear cut. On one hand, an efficient risk transfer may enable banks to increase their stability by allowing them to shift risks outside their balance sheet as well as achieving portfolio and funding diversifications more easily (Instefjord, 2005; Wagner, 2007). On the other hand, banks may also become riskier whether they use the funding obtained from securitization to grant riskier loans, keep the riskiest tranche in a securitization, and/or have to (explicitly or implicitly) guarantee securitization vehicles. As such, the effect of securitization on bank risk is not theoretically straightforward and it remains an open empirical question.

The empirical literature is mixed regarding securitization risks. Based on 73 European CDOs, Franke and Krahnen (2005) find that European securitization markets are associated with an increase in the average beta. Low risk banks are more likely to securitize (Minton, 2004), whereas Bannier and Hansel (2007) find that securitizations can be structured to substantially increase bank systemic risk.

A first stream of papers focuses on credit risk indicating that securitizing banks lend more to risky borrowers, have less diversified portfolios, hold less capital, retain riskier loans, and are more aggressive in loan pricing (Kara et al., 2016; Casu et al., 2013; Michalak and Uhde, 2012;

Barth et al., 2012; Affinito and Tagliaferri, 2010; Hansel and Krahnen, 2007; Franke and Krahnen, 2006; Cebenoyan and Strahan, 2004). Some studies focusing on mortgages find that banks active in securitization originate low quality loans, have higher default rates, and lose their screening and monitoring incentives (Chava and Purnanandam, 2011; Keys et al., 2010; Dell'Ariccia et al., 2010; Mian and Sufi, 2009). However, there are also papers finding that securitization reduces insolvency risk, increases profitability, provides liquidity and leads to greater supply of loans (Loutskina, 2011; Loutskina and Strahan, 2009; Altunbas et al., 2009; Jiangli and Pritsker, 2008).

A second stream of literature focuses on systematic risk. Specifically, various papers show that banks display higher betas after securitization deals (Iglesias-Casal et al., 2016; Battaglia et al., 2014, Nijiskens and Wagner, 2011; Michalak and Uhde, 2010; Hansel and Krahnen, 2007) due to two reasons: first, banks may reinvest funds obtained by securitizing assets in riskier projects; second, banks may retain the first-loss piece (exhibiting a higher probability of failure) and transfer less risky senior tranches to external investors. A somewhat different view is supported by Wu and Hong (2010), who distinguish between systematic and idiosyncratic risk: asset securitization reduces banks' systematic risk exposure, but there is no evidence of increasing idiosyncratic risk.

A third stream of literature focuses on systemic risk (Battaglia and Gallo, 2013; Michalak and Uhde, 2012; Nijskens and Wagner, 2011; Gorton and Metrick, 2012; Berger et al., 2015). Generally, these papers find that securitization increase systemic risk, even if the banks' individual risk itself does not rise. This is because securitization allows banks to shed idiosyncratic exposures, such as the specific risk associated with their area of lending. Moreover, securitization also exposes banks to bigger funding risks, 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, by amplifying the risk of a systemic crisis in the financial system (Acharya and Yorulmazer, 2008; Elsinger et al., 2006).

2.2 Crash Risk Literature Review

As outlined in previous studies (e.g., Jin and Myers, 2006), managers tend to withhold bad news for as long as possible. However, there is an upper limit to the amount of bad news that managers can absorb. When the accumulated bad news reaches this upper limit, it will come out all at once, leading to a large and sudden price decline. Crash risk may be linked to several firm features, from the opacity of reporting to default risk (for an extensive literature review on crash risk, see Habib et al., 2017). In the literature, bad news tends to stem from two areas: (1) career concerns; (2) lower stock price decreasing equity compensation. To safeguard their job and protect their compensation, executives tend to withhold bad news (Kothari et al., 2009).

Large negative stock returns, or stock price crashes, are more common than large positive stock price movements (Chen et al., 2001; Hong and Stein, 2003). Chen et al (2001) find that firms with high return skewness in year T are likely to have high return skewness in year T+1. Hutton et al (2009) document a positive relation between firm size and crash risk. Most previous crash risk studies focus on one country, namely the US. And they tend to investigate how firm actions or characteristics affect stock price crash risk (Hutton et al., 2009; Kim et al., 2011 a, b).

Habib et al., (2017) provide a literature review of crash price research. More recent research links crash risk with innovation strategy (Jia, 2018), with national culture (An et al., 2018) and product market competition (Li and Zhan, 2018).

2.3 Hypothesis Development

Overall, there is no conclusive evidence regarding the relationship between securitization and bank risk perceived by investors. There is also a dearth of papers focusing on tail risk measures (or crash risk and expected shortfall measures). Overall, the literature does not provide consistent evidence of the relationship between securitization and bank risk. Moreover, none provide causal evidence that securitization decreases or increases bank risk. Our aim is to understand if investors perceive that securitization deals make banks more subject to extreme events. Specifically, we realize that investors and practitioners do not recognize downside and upside risks in the same manner, as what appears to happen in classic market risk measures (Farago and Tédongap, 2018; Kosmidou et al., 2017). Consequently, we focus on the effect of securitization on crash risk by using various indicators capturing the probability of extreme negative events.

The sign of the relationship is not theoretically straightforward either: on one hand, there are reasons (e.g., banks use liquid funds obtained by securitization to lend more to risky borrowers, and retain riskier loans) to expect that securitization is associated with higher crash risk (H_1). On the other hand, a competing hypothesis is that securitization is associated with lower crash risk (H_{1A}) by selling risky loans and obtaining liquid funds.

We also test if the relationship between securitization and crash risk differs for high and low-risk securitizations. More specifically, we identify a subsample of low-risk securitizations (i.e., loans with a high degree of standardization, collateralization and granularity) and high-risk securitizations[8] (i.e., high number of complex loan arrangements, which are typically difficult to evaluate for potential investors and, hence, are perceived as riskier by them). This leads to the following hypotheses:

H1: Securitization activity decreases the originators' crash risk

As some determinants of securitization activity are likely to be determined by the riskiness of the respective underlying loan portfolio (Farruggio and Uhde, 2015; Cardone-Riportella et al., 2010; Panetta and Pozzolo, 2010; Uzun and Webb, 2007), in order to control for the specific effect of differences in the underlying asset pool of a securitization transaction, we develop a further hypothesis:

H2: The relationship between securitization and crash risk differs for high and low-risk securitizations

High risk securitizations: transactions when the underlying asset type is a collateralized debt obligation - CDO (high yield bonds, corporate loans, investment grade bonds, preferred stock or structured finance credit); low risk securitizations: transactions when the underlying asset type is not a CDO.

[8] Farruggio and Uhde (2015)

3. Empirical Methodology

Our identification strategy addresses the issue of potential endogeneity in establishing a causal relationship between securitization and the volatility of a bank's stock returns. We consider two main problems: 1) reverse causality (i.e., the possibility that bank managers make use of securitization in anticipation of future stock return volatility), and 2) omitted variable bias (i.e., the possibility that unobserved factors bias our conclusions on the relationship between securitization and stock price risk).

We follow some recent papers proposing a dynamic panel data approach to address the endogeneity issue (Fresard, 2010; Dessaint et al., 2017; Gopalan, et al., 2017). Our main variable of interest is securitization (Sec) and is included in the model at the time of the deal (date *t*), one year before (date *t*-1), and one year after (date *t*+1). Several additional variables are created. $Sec_{i,t}$ is the volume of securitization in the current year *t*. $Post\_Sec_{i,t}$ is the volume of securitization in the prior year. Finally, $Pre\_Sec_{i,t}$ is the volume of securitization that the bank will have next year[9]. Specifically, we run the following regression:

$$Y_{i,t} = \alpha + \beta_1 Pre\_Sec_{i,t} + \beta_2 Sec_{i,t} + \beta_3 Post\_Sec_{i,t} + \gamma' Controls_{i,t-1} + A_i + B_t + \eta_{i,t} \quad (1)$$

where the dependent variable, $Y_{i,t}$, is a measure of bank *i*'s stock return volatility in year *t*. The contemporaneous relationship between securitization and bank risk is measured by the coefficient β_2 while β_3 measure the effect of securitization on the bank risk in the following year.

[9] This is based on the jargon of the dynamic model. When we say POST, we mean what happens to the outcome variable (crash risk) the year after securitization. So, if we are studying crash risk in 2015, the POST variable represents the effect of securitization done in 2014 one year later (in 2015). So, from the operational point of view, it is a lag. The opposite holds for PRE

We can interpret this coefficient in a causal sense if β_1 is not statistically significant at the 10% confidence level or less. If β_1 is statistically significant, this signals a relationship between bank risk at time *t* and the decision to securitize assets at time *t+1*. In this case, we have a reverse causality problem and therefore cannot interpret β_3 in a causal way. In accordance with prior literature, our model also controls for some bank specific characteristics. We consider the log of total assets (SIZE) and a risk-sensitive measure of capitalization (TIER 1 ratio). At the country level, we consider the level of prices (INFLATION). To alleviate a potential missing (or omitted) variables problem, we also include in our model bank- and year-fixed effects. We calculate standard errors clustered at the country level.

As a second step, we run a model considering the potential impact of the global financial crisis. We include a dummy variable, named CRISIS, taking the value of 1 for the years between 2008 and 2013. The beginning of the global financial crisis is considered to be the collapse of Lehman brothers in September 2008. Since we are investigating sample of European banks, we also consider the Eurozone sovereign debt crisis, which was in its most acute phase until 2013. This crisis dummy enters the model in interaction with all our variables of interest related to securitization, in order to understand whether the impact of securitization on bank risk was different in times of crisis. A description of the variables used is presented in Appendix 1.

4. Data and variables measurement

Since securitization deals are made mostly by large listed banks, we draw the data from the Thomson Reuters database. We select all securitization deals performed by European banks that are included in the Euro Stoxx 600[10]. This selection criteria are consistent with past papers (Minton et al., 2004; Michalack and Udhe, 2010; Farruggio and Udhe, 2015) and enables us to obtain an homogenous sample, not biased by differences in accounting standards, loan portfolio management techniques and business policies. The sample is based on 11 EU countries: Germany, Denmark, Spain, France, Great Britain, Greece, Italy, Netherlands, Portugal, Sweden and Turkey.

Our sample covers the period from 3 January 2000 to December 2017. We start with an initial sample of 46 banks, but we exclude some banks due to data availability. Specifically, we have removed: a) banks that carried out securitization transactions through other legal entities (for example, Banca Fineco transactions are structured by its ultimate owner Unicredit), b) banks that did not disclose all the required information on their securitization transactions to the database provider, c) banks that have carried out a low volume of securitization transactions and are not included in the world ranking provided by the database. Moreover, a survivorship bias is likely to occur due to mergers and acquisitions occurring within the European banking industry during the sample period. Since some of our sample banks no longer exist we address this issue by omitting those involved in a merger or acquired by other banks and retain the new combined entity or the acquirer in our final sample.

After these adjustments, our sample drops to 35 listed banks for a total number of 433 observations. All of our sample securitizing banks are frequent issuers, with the exception of Nordea and Swed bank (for which only one security transaction is recorded) leading to a total of 7,096 securitization transactions over the entire investigation period. If a bank securitizes several

[10]The composition of the index refers to 5 December 2017. We omit securitization transactions from banks located in Ireland, Czech Republic and Norway, since we are not able to assign securitization transactions to respective originating banks in these countries.

times during the same year, the volumes of the respective multiple transactions are accumulated and included in the model.

We retrieve bank balance sheet data and the historical stock prices from Datastream, whilst macroeconomic data are drawn from the World Bank database. All the explanatory variables are included in our regressions on an annual basis.

With regards to the originating bank size, performance and capitalization, we employ the natural logarithm of total assets (SIZE) and the ratio of the bank's Tier 1 capital to risk weighted assets (TIER 1) respectively. We also include the inflation rate (INF) as a macroeconomic control variable for the state of the economy to examine differences in bank risk taking due to national characteristics.

Related to securitization activities and our key independent variables, we adopt three different variables: SEC, SEC_HR and SEC_LR. The first one, SEC, is the ratio of a banks' cumulative securitization volume to total assets, while SEC_HR and SEC_LR refer to the riskiness of the underlying assets. Specifically we define high-risk securitizations transactions when the underlying asset type is a collateralized debt obligation - CDO (high yield bonds, corporate loans, investment grade bonds, preferred stock or structured finance credit) and low-risk securitizations when the underlying asset type is not a CDO.

Following recent studies, we consider several measures of crash risk (Chen et al., 2001; Jin and Myers, 2006; Hutton et al., 2009; Callen and Fang, 2013; Dewally and Shao, 2013). Following Hutton et al. (2009) and Dewally and Shao (2013), we run an augmented market model, including lag and lead terms for market returns to remove the impact of market returns and obtain firm specific returns:

$$r_{i,t} = \alpha_i + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_5 r_{m,t+2} + \varepsilon_{i,t} \qquad (2)$$

where $r_{i,t}$ is the date t return for bank i in week t and $r_{m,t}$ is the market index return (MSCI Europe All Cap). From this model, we obtain bank-specific returns as the residual from regression (2).

Following prior research (e.g., Hutton et al. (2009)), a crash occurs when the daily bank-specific return is 3.09 standard deviations below the mean of the bank's residual returns. The opposite event (i.e., the daily bank-specific return is 3.09 standard deviations above the mean of the bank's residual returns) is defined as a jump. We measure the difference between the number of crashes and the number of jumps in a given year (*CRASH_JUMP*). Following Hutton et al. (2009), Callen and Fang (2015) and Jia (2018), we also take into account the negative conditional skewness (NCSKEW), which is calculated as:

$$NCSKEW_{i,t} = -\frac{n(n-1)^{3/2} \sum \varepsilon_{i,t}^3}{(n-1)(n-2)(\sum \varepsilon_{i,t}^2)^{3/2}} \qquad (3)$$

In Equation 3, NCSKEW measures left-tail thickness, and is scaled by the standard deviation of the returns. The denominator serves as a normalization factor. The scaling allows for us to compare stocks with different volatilities. The variable n measures the number of observations on weekly returns. The minus sign in front of the equation allows us to interpret an increase in *NCSKEW* as corresponding to a stock having a more left-skewed distribution and thus being more prone to crash.

Finally, we include an alternative measure that does not involve the third moment and, as a result, is less likely to be excessively affected by a small number of extreme returns. We calculate the down-to-up volatility (*DUVOL*) crash risk measure is defined as follows:

$$DUVOL_{i,t} = \ln\left(\frac{(n_j - 1)\sum_{crash}\varepsilon_{i,t}^2}{(n_c - 1)\sum_{jump}\varepsilon_{i,t}^2}\right) \quad (4)$$

where n_j and n_d are the number of "jump" and "crash" days over the fiscal year. Then we calculate the standard deviation for the ''jump'' and ''crash'' samples. Next we compute the natural log of the standard deviation of the ''crash'' sample to the standard deviation of the ''jump'' sample. DUVOL is a return asymmetry measure that does not involve third moments and is less likely to be overly influenced by a handful of extreme weekly returns. A higher value for DUVOL corresponds to a stock being more ''crash prone.''

Table 1 provides summary statistics of the variables used in the main analyses. On average, a bank has a crash risk NCSKEW of 0.00725, a DUVOL of 0.00218 and a CRASH_JUMP of -0.009. In terms of SEC (the ratio of a bank's cumulative securitization volume to total assets) is 0.01395, for low risk securitizations it is 0.01239 and for high risk securitizations it is 0.00156. The average bank in our sample has an average Tier 1 capital ratio of 9.94% and a natural logarithm of assets of 26.65.

[INSERT TABLE ONE ABOUT HERE]

Table 2 provides the correlation matrix results for the main variables used in subsequent analyses. The two crash risk variables NCSKEW and DUVOL have a high correlation of 0.88, which is comparable to the values reported in previous studies (Chen et al., 2001; Callen and Fang, 2015; Kosmidou, 2017 and Jia, 2018). NCSKEW is also strongly positively correlated with the CRASH_JUMP variable. These measures appear to capture the same underlying character, even though they are constructed differently from firm-specific weekly returns. NCSKEW, DUVOL and CRASH_JUMP all have a negative correlation with SEC and with low risk securitizations (SEC_LR). However, they all have a positive correlation with high risk securitizations (SEC_HR). Table 2 appears to provide some preliminary evidence that supports our first hypothesis. However, we consider this evidence suggestive and to draw more substantial inferences we will rely on subsequent multivariate analyses.

[INSERT TABLE TWO ABOUT HERE]

5. Results

First, we comment on the general regression model presented in equation (1) using as dependent variables several different measures of crash risk. We use a dynamic panel data specification to address the issue of reverse causality.

General regression results are shown in Table 3. We consider a more parsimonious series of models (1a, 2a, and 3a) and a more complete version including control variables at the bank and country levels (1b, 2b, and 3b). There is no evidence of a reverse causality problem, since the coefficients on *PRE_SEC* are always statistically insignificant at the 10% confidence level or less. This implies that banks do not securitize assets in anticipation of an increase in their risk perceived by investors. Consequently, we can interpret the coefficients of *SEC* and *POST_SEC* in a causal way. The contemporaneous effect is always negative and statistically significant at the 10% confidence level or less for all crash risk indicators (*CRASH_JUMP*, *NCSKEW*, and *DUVOL*), except that in Model 3a (the parsimonious model for down-to-up volatility). The coefficient for *POST_SEC* is positive and not statistically significant at the 10% confidence level or less.

Results shown in Table 3 are also economically meaningful. Specifically, we find that an increase of one standard deviation of the *SEC* variable (equal to about 2.84%) leads to a decrease of *CRASH_JUMP* of about 12.6% and 12.5% (respectively in Models 1a and 1b); to a decrease of *NCSKEW* of about 9.38% and 9.50% (respectively in Models 2a and 2b), and to a decrease of *DUVOL* of about 5.43% and 5.60% (respectively in Models 3a and 3b).

For the more complete version of the model, including control variables, we also run a test on the linear combination of *SEC* and *POST_SEC*, finding that the overall effect is negative and statistically significant at the 10% confidence level only for crashes minus jumps (*CRASH_JUMP*), while it is not statistically significant at the 10% confidence level or less for the negative conditional skewness (NCSKEW) and the down-to-up volatility (*DUVOL*) (see Table 3).

Our results for DUVOL are consistent with those obtained from previous studies, finding a reduction in the market risk of the banks in the year of the securitization (negative contemporaneous effect), but an increase in the bank risk subsequent to the securitization activity (positive post-securitization effect). The contemporaneous risk-reduction effect of securitization is likely to be determined by the technique of tranching the securitization's issues, allowing banks to hold less risk simply due to diversification and more tradability (Berger et al., 2015). 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, 2008).

[INSERT TABLE THREE ABOUT HERE]

A post-event increasing market risk 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 (Franke and Krahnen, 2005; Krahnen and Wilde, 2006; Hansel and Krahnen, 2007; Nijskens and Wagner, 2011; Battaglia and Gallo, 2013; Battaglia et al., 2014). Moreover, the increased liquidity subsequent to the securitization activity improves banking stability. Consequently, banks may have an incentive to behave more aggressively in acquiring new risks (Jiangli and Pritsker, 2008; Instefjord, 2005; Rajan, 2005).

Second, we distinguish the underlying asset portfolio of securitization transactions, running model in equation (1), respectively, for high and low-risk securitizations. For high-risk securitization, results are shown in Table 4. Different from the general model, we have some evidence of reverse causality problems, since the coefficient of *PRE_SEC* is positive and statistically significant at the 5% confidence level for crashes minus jumps (*CRASH_JUMP*); for all other risk measures, there are no significant results. More specifically, high risk securitization transactions exhibit different effects during the pre-securitization year, providing some evidence that banks may securitize opaque assets in anticipation of an increase in crash risk. Moreover, this evidence is likely to be determined also by the behavior of investors (Panetta and Pozzolo, 2010), who attribute a lower degree of visibility, transparency and quality to the underlying assets of these transactions and, in turn, anticipate an increase in the banks' risk exposure.

[INSERT TABLE FOUR ABOUT HERE]

Finally, we run the model in equation (1) for low-risk securitizations and the results are shown in Table 5. Our findings are very similar to the general model in Table 2. More specifically, the low-risk subsample confirms the results of the overall sample: there is evidence of a contemporaneous risk-reduction effect of securitization and a post-event market increasing risk. However, in the case of low-risk securitization, the risk reduction effect is larger and the overall effect of SEC+POST_SEC is negative and statistically significant at the 10% confidence level for both crashes minus jumps and down-to-up volatility.

[INSERT TABLE FIVE ABOUT HERE]

Finally, in Table 6, we consider a second specification to test possible differences between the normal times and crisis periods. We run the model for the entire securitization volume, including a dummy for the crisis period and an interaction of this dummy with all variables measuring securitization. As in the general model, we do not find evidence of reverse causality, since both PRE_SEC and its interaction with the crisis dummy are not statistically significant. During normal times (i.e., non-crisis periods), results are very similar to the general models shown in Table 3: there is a contemporaneous risk reduction effect, followed by an increase in market risk. Overall, this leads to a weak risk reduction effect, which is statistically significant at the 10% confidence level only for crashes minus jumps (*CRASH_JUMP*). During crisis periods, we have to consider also the coefficients of the interactions with the crisis dummies. The interaction between the crisis dummy and the contemporaneous effect is always positive, while the one with the post securitization variable is negative and statistically significant in 4 out of 6 models at the 10% confidence level or less. Testing a linear combination of the coefficients during normal times (SEC and POST_SEC) and their interaction with the crisis dummy (SEC*CRISIS and POST_SEC*CRISIS), we find that, overall, securitization during crisis periods does not produce any risk reduction effect.

[INSERT TABLE SIX ABOUT HERE]

6. Robustness checks

As a robustness check, we run our models considering more established measures of tail risk, always keeping in mind that downside risk is priced differently from upside uncertainty and that investors pay particular attention on extreme events.

We take into account the most common indicators of tail risk i.e., Value at Risk (*VaR*) and Expected Shortfall (*ES*), both measured from historical simulation with a confidence level of 97.5% and a one-day holding period, using one year of stock daily returns (Hull, 2012).

Results are shown in Table 7 for the overall model and in Tables 8 and 9 for high and low securitizations, respectively. Specifically, referring to Table 7, we show that an increase of one standard deviation of the *SEC* variable (equal to about 2.84%) leads to a decrease of the VaR of about 9.41‰ and 9.17‰ respectively in Models 1a and 1b, and to a decrease of the ES of about 9.51‰ and 9.26‰ respectively in Models 2a and 2b. Overall, our findings are strongly consistent with the main models, confirming the difference between high-risk and low-risk securitization.

[INSERT TABLE SEVEN ABOUT HERE]

[INSERT TABLE EIGHT ABOUT HERE]

[INSERT TABLE NINE ABOUT HERE]

7. Conclusions

We have examined a relatively unexplored area of the literature, namely the potential relationship between securitization and stock price crash risk. Specifically, we examine whether securitizing banks tend to be more prone to crash risk. Our sample draws on European commercial listed banks included in the Euro Stoxx 600 index and covers all securitization activity during the period 2000-2017.

We answer two main research questions. Does securitization activity decrease the originators' risk? We show a reduction in bank risk in the year a bank securitizes (a negative contemporaneous effect), but an increase in risk subsequent to the securitization issuance (positive post-securitization effect). This is consistent with past evidence, showing that investors appreciate the transfer of risk, but also recognize that banks often retain the first-loss piece and use the freed up liquidity for riskier projects.

Second, we examine whether the relationship between securitization and risk differs for high and low-risk securitizations. We find that, in high-risk securitizations, banks may securitize opaque assets in anticipation of an increase in crash risk, pointing to a reverse causality problem. In low-risk securitizations, our findings are very similar to the results of the overall sample, and statistically stronger: there is evidence of a contemporaneous risk-reduction effect of securitization and a post-event market increasing risk. Finally, we also show that the risk reduction effect is weaker in the crisis period relative to normal times.

Our paper has important implications for regulators as they try to revive European securitization markets. To curtail crash risk, regulators should closely monitor banks' crash related risk taking and securitization behavior.

Table 1 – Descriptive Statistics

In this table we report the mean, standard deviation, minimum and maximum of the variables used in our empirical analysis.

Panel A – Descriptive statistics

Variables	Obs	Mean	Std	Min	Max
SEC	433	0.01395	0.02843	0.00000	0.24499
SEC_HR	433	0.00156	0.00463	0.00000	0.04610
SEC_LR	433	0.01239	0.02498	0.00000	0.19889
CRASH_JUMP	433	-0.00924	0.57728	-1.00000	1.00000
NCSKEW	433	0.00725	0.58218	-1.15400	1.40243
DUVOL	433	0.00218	0.40641	-0.76289	0.90288
VAR_0975	433	0.11236	0.06271	0.03357	0.29494
ES_0975	433	0.11386	0.06354	0.03388	0.29700
SIZE	433	26.65977	1.26175	22.07486	28.56660
TIER1_RATIO (%)	433	9.94391	3.19601	6.20000	23.80000
INF	433	0.02561	0.97789	-2.06211	2.26643

Table 2 – Correlation matrix

	Sec	Sec_hr	Sec_lr	Crash_jump	Ncskew	Duvol	Var_0975	Es_0975	Size	Tier1_	Inf
SEC	1.0000										
SEC_HR	0.7826	1.0000									
SEC_LR	0.9933	0.7055	1.0000								
CRASH_JUMP	-0.0037	0.0236	-0.0086	1.0000							
NCSKEW	-0.0254	0.0167	-0.0321	0.7819	1.0000						
DUVOL	-0.0409	0.002	-0.0469	0.5919	0.8816	1.0000					
VAR_0975	-0.1769	-0.1419	-0.1751	0.2112	0.2853	0.2383	1.0000				
ES_0975	-0.1778	-0.1425	-0.176	0.2094	0.284	0.2365	0.9998	1.0000			
SIZE	0.1617	0.1309	0.1598	0.1317	0.1464	0.0828	0.1364	0.1358	1.0000		
TIER1_RATIO (%)	-0.1085	-0.0888	-0.1071	-0.0519	-0.0261	-0.0739	-0.1067	-0.1059	0.0531	1.0000	
INF	0.0992	0.0837	0.0974	0.1068	0.0934	0.117	-0.0343	-0.0344	-0.1087	-0.4272	1.0000

Table 3 – Securitization and stock price crash risk – General Model

This table reports results from regressions in the form of equation (1). The dependent variable is a measure of stock price crash risk. The dependent variable is the number of crashes minus the number of jumps in Models 1a and 1b, negative conditional skewness in Models 2a and 2b, down-to-up volatility in Models 3a and 3b. The main variables of interest are those identifying the use of securitization as defined in Table 1. All continuous variables are standardized and winsorized at the 1 and 99 percentiles. Control variables are Size, Tier 1 ratio (which are lagged one year) and inflation. Robust standard errors clustered at the country level are reported in parentheses. ***, **, * denotes that estimates are statistically significant at the 1, 5 and 10% levels.

VARIABLES	(1a) crash_jump	(1b) crash_jump	(2a) ncskew	(2b) ncskew	(3a) duvol	(3b) duvol
PRE_SEC	0.0586	0.0695	0.0196	0.0253	0.00440	0.00949
	(0.0397)	(0.0418)	(0.0322)	(0.0322)	(0.0335)	(0.0333)
SEC	-0.126**	-0.125**	-0.0938**	-0.0950**	-0.0543	-0.0560*
	(0.0424)	(0.0416)	(0.0395)	(0.0378)	(0.0303)	(0.0288)
POST_SEC	0.0417	0.0424	0.0436	0.0454	0.0194	0.0215
	(0.0582)	(0.0607)	(0.0481)	(0.0480)	(0.0294)	(0.0278)
$SIZE_{t-1}$	-	0.286*	-	0.110	-	0.0847
		(0.146)		(0.142)		(0.0997)
$TIER\ 1_{t-1}$	-	-0.0797**	-	-0.0491	-	-0.0516
		(0.0339)		(0.0758)		(0.0402)
INF_t	-	0.0409	-	0.0395	-	0.0437
		(0.0335)		(0.0408)		(0.0347)
Constant	-0.186	-0.235	-0.0997	-0.147	-0.0344	-0.0894
	(0.106)	(0.130)	(0.159)	(0.186)	(0.101)	(0.105)
Observations	433	433	433	433	433	433
R-squared	0.131	0.141	0.126	0.129	0.088	0.095
Number of id	37	37	37	37	37	37
Bank fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
LINEAR COMBINATION						
SEC + POST_SEC		-0.0824*		-0.0496		-0.0344

Table 4 – High-risk securitization and stock price crash risk

This table reports results from regressions in the form of equation (1). The dependent variable is a measure of stock price crash risk. The dependent variable is the number of crashes minus the number of jumps in Models 1a and 1b, negative conditional skewness in Models 2a and 2b, down-to-up volatility in Models 3a and 3b. The main variables of interest are those identifying the use of high-risk securitization as defined in Table 1. All continuous variables are standardized and winsorized at the 1 and 99 percentiles. Control variables are Size, Tier 1 ratio (which are lagged one year) and inflation. Robust standard errors clustered at the country level are reported in parentheses. ***, **, * denotes that estimates are statistically significant at the 1, 5 and 10% levels.

VARIABLES	(1a) crash_jump	(1b) crash_jump	(2a) ncskew	(2b) ncskew	(3a) duvol	(3b) duvol
PRE_SEC_HR	0.0548**	0.0586**	0.0108	0.0127	0.00614	0.00766
	(0.0241)	(0.0241)	(0.0197)	(0.0192)	(0.0220)	(0.0240)
SEC_HR	-0.0515	-0.0465	-0.0166	-0.0143	-0.0154	-0.0135
	(0.0414)	(0.0402)	(0.0366)	(0.0361)	(0.0240)	(0.0241)
POST_SEC_HR	0.00247	0.000477	0.0114	0.0107	0.0246	0.0240
	(0.0319)	(0.0331)	(0.0358)	(0.0371)	(0.0205)	(0.0213)
$SIZE_{t-1}$	-	0.304**	-	0.135	-	0.104
		(0.125)		(0.142)		(0.0952)
$TIER\ 1_{t-1}$	-	-0.0762*	-	-0.0478	-	-0.0495
		(0.0350)		(0.0735)		(0.0395)
INF_t	-	0.0387	-	0.0385	-	0.0439
		(0.0392)		(0.0432)		(0.0382)
Constant	-0.182	-0.226	-0.0928	-0.136	-0.0235	-0.0751
	(0.102)	(0.129)	(0.156)	(0.183)	(0.102)	(0.105)
Observations	433	433	433	433	433	433
R-squared	0.128	0.138	0.120	0.124	0.084	0.092
Number of id	37	37	37	37	37	37
Bank fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
LINEAR COMBINATION						
SEC_HR + POST_SEC_HR		-0.0460		-0.0037		0.0105

Table 5 – Low-risk securitization and stock price crash risk

This table reports results from regressions in the form of equation (1). The dependent variable is a measure of stock price crash risk. The dependent variable is the number of crashes minus the number of jumps in Models 1a and 1b, negative conditional skewness in Models 2a and 2b, down-to-up volatility in Models 3a and 3b. The main variables of interest are those identifying the use of low-risk securitization as defined in Table 1. All continuous variables are standardized and winsorized at the 1 and 99 percentiles. Control variables are Size, Tier 1 ratio (which are lagged one year) and inflation. Robust standard errors clustered at the country level are reported in parentheses. ***, **, * denotes that estimates are statistically significant at the 1, 5 and 10% levels.

VARIABLES	(1a) crash_jump	(1b) crash_jump	(2a) ncskew	(2b) ncskew	(3a) duvol	(3b) duvol
PRE_SEC_LR	0.0434	0.0549	0.0150	0.0209	0.00127	0.00659
	(0.0430)	(0.0460)	(0.0337)	(0.0344)	(0.0337)	(0.0335)
SEC_LR	-0.119**	-0.119**	-0.0975**	-0.0991**	-0.0541*	-0.0562*
	(0.0409)	(0.0406)	(0.0386)	(0.0376)	(0.0298)	(0.0289)
POST_SEC_LR	0.0411	0.0427	0.0429	0.0452	0.0117	0.0143
	(0.0574)	(0.0598)	(0.0453)	(0.0446)	(0.0287)	(0.0264)
$SIZE_{t-1}$	-	0.281*	-	0.108	-	0.0822
		(0.148)		(0.142)		(0.100)
$TIER\ 1_{t-1}$	-	-0.0808**	-	-0.0499	-	-0.0522
		(0.0340)		(0.0766)		(0.0403)
INF_t	-	0.0405	-	0.0394	-	0.0433
		(0.0323)		(0.0400)		(0.0341)
Constant	-0.185	-0.235	-0.102	-0.150	-0.0373	-0.0927
	(0.106)	(0.131)	(0.158)	(0.186)	(0.101)	(0.104)
Observations	433	433	433	433	433	433
R-squared	0.130	0.140	0.127	0.130	0.089	0.096
Number of id	37	37	37	37	37	37
Bank fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
LINEAR COMBINATION						
SEC_LR + POST_SEC_LR		-0.0763*		-0.0539		-0.0419*

Table 6 – Securitization and stock price crash risk – Crisis Model

This table reports results from regressions in the form of equation (2). The dependent variable is a measure of stock price crash risk. The dependent variable is the number of crashes minus the number of jumps in Models 1a and 1b, negative conditional skewness in Models 2a and 2b, down-to-up volatility in Models 3a and 3b. The main variables of interest are those identifying the use of securitization as defined in Table 1 and the interaction with crisis. All continuous variables are standardized and winsorized at the 1 and 99 percentiles. Control variables are Size, Tier 1 ratio (which are lagged one year) and inflation. Robust standard errors clustered at the country level are reported in parentheses. ***, **, * denotes that estimates are statistically significant at the 1, 5 and 10% levels.

VARIABLES	(1a) crash_jump	(1b) crash_jump	(2a) ncskew	(2b) ncskew	(3a) duvol	(3b) duvol
PRE_SEC	0.0811	0.0914	0.0448	0.0499	0.00967	0.0150
	(0.0636)	(0.0650)	(0.0487)	(0.0484)	(0.0424)	(0.0421)
SEC	-0.227**	-0.230**	0.222**	-0.225**	-0.130*	-0.133*
	(0.0878)	(0.0897)	(0.0751)	(0.0759)	(0.0609)	(0.0612)
POST_SEC	0.135*	0.140*	0.165**	0.170***	0.0998*	0.104**
	(0.0641)	(0.0629)	(0.0537)	(0.0514)	(0.0463)	(0.0429)
$SIZE_{t-1}$	-	0.294*	-	0.108	-	0.108
		(0.139)		(0.133)		(0.0984)
$TIER\ 1_{t-1}$	-	-0.0784**	-	-0.0500	-	-0.0491
		(0.0351)		(0.0767)		(0.0416)
INF_t	-	0.0423	-	0.0430	-	0.0449
		(0.0315)		(0.0395)		(0.0331)
*PRE_SEC*CRISIS*	-0.115	-0.109	-0.111	-0.104	0.00401	0.0120
	(0.174)	(0.183)	(0.134)	(0.142)	(0.0486)	(0.0509)
*SEC*CRISIS*	0.292	0.276	0.356	0.354	0.104	0.102
	(0.386)	(0.370)	(0.284)	(0.278)	(0.142)	(0.136)
*POST_SEC*CRISIS*	-0.166	-0.178	-	-0.222**	-	-
			0.217**		0.159**	0.164**
	(0.101)	(0.107)	(0.0915)	(0.0953)	(0.0642)	(0.0656)
Constant	-0.179	-0.226*	-0.0899	-0.140	-0.0271	-0.0774
	(0.107)	(0.124)	(0.158)	(0.182)	(0.101)	(0.104)
Observations	433	433	433	433	433	433
R-squared	0.141	0.151	0.142	0.145	0.100	0.109
Number of id	37	37	37	37	37	37
Bank fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
LINEAR COMBINATION						
a) SEC+POST_SEC		-0.0894*		-0.0555		-0.0289
*b) SEC*CRISIS+POST_SEC*CRISIS*		0.0985		0.1323		-0.0619
c) A+B		0.0091		0.0768		-0.0907

Table 7 – Robustness check: Securitization and stock price tail risk (General Model)

This table reports results from regressions in the form of equation (1). The dependent variable is a measure of stock price tail risk. The dependent variable is Value at Risk, one-day, 97.5% in Models 1a and 1b, and Expected Shortfall in Models 2a and 2b. The main variables of interest are the indicator variables identifying the use of securitization as defined in Table 1. All continuous variables are standardized and winsorized at the 1 and 99 percentiles. Control variables are Size, Tier 1 ratio (which are lagged one year) and inflation. Robust standard errors clustered at the country level are reported in parentheses. ***, **, * denotes that estimates are statistically significant at the 1, 5 and 10% levels.

VARIABLES	(1a) var_0975	(1b) var_0975	(2a) es_0975	(2b) es_0975
PRE_SEC	0.00131	0.00216	0.00141	0.00225
	(0.00257)	(0.00289)	(0.00263)	(0.00296)
SEC	-0.00941**	-0.00917**	-0.00951**	-0.00926**
	(0.00307)	(0.00294)	(0.00310)	(0.00297)
POST_SEC	0.00266	0.00253	0.00261	0.00248
	(0.00269)	(0.00262)	(0.00274)	(0.00266)
$SIZE_{t-1}$	-	0.0269*	-	0.0268
		(0.0148)		(0.0152)
$TIER\ 1_{t-1}$	-	-0.00731	-	-0.00749
		(0.00625)		(0.00633)
INF_t	-	0.00145	-	0.00147
		(0.00279)		(0.00284)
Constant	0.127***	0.124***	0.131***	0.128***
	(0.0106)	(0.0120)	(0.0114)	(0.0128)
Observations	433	433	433	433
R-squared	0.697	0.703	0.695	0.702
Number of id	37	37	37	37
Bank fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
LINEAR COMBINATION				
SEC + POST_SEC		-0.0066**		-0.0068**

Table 8 – Robustness check: High-risk securitization and stock price tail risk

This table reports results from regressions in the form of equation (1). The dependent variable is a measure of stock price tail risk. The dependent variable is Value at Risk, one-day, 97.5% in Models 1a and 1b, and Expected Shortfall in Models 2a and 2b. The main variables of interest are the indicator variables identifying the use of high-risk securitization as defined in Table 1. All continuous variables are standardized and winsorized at the 2.5 and 97.5 percentiles. Control variables are Size, Tier 1 ratio (which are lagged one year) and inflation. Robust standard errors clustered at the country level are reported in parentheses. ***, **, * denotes that estimates are statistically significant at the 1, 5 and 10% levels.

VARIABLES	(1b) var_0975	(1b) var_0975	(2b) es_0975	(2b) es_0975
PRE_SEC_HR	-0.00191*	-0.00163	-0.00192*	-0.00165
	(0.000971)	(0.00113)	(0.000986)	(0.00115)
SEC_HR	-0.00377*	-0.00331*	-0.00376*	-0.00329*
	(0.00176)	(0.00163)	(0.00177)	(0.00164)
POST_SEC_HR	0.00329	0.00307	0.00316	0.00294
	(0.00199)	(0.00198)	(0.00198)	(0.00197)
$SIZE_{t-1}$	-	0.0272*	-	0.0270*
		(0.0141)		(0.0145)
$TIER\ 1_{t-1}$	-	-0.00724	-	-0.00743
		(0.00624)		(0.00633)
INF_t	-	0.00135	-	0.00137
		(0.00289)		(0.00293)
Constant	0.129***	0.126***	0.133***	0.129***
	(0.0107)	(0.0119)	(0.0115)	(0.0127)
Observations	433	433	433	433
R-squared	0.694	0.701	0.692	0.699
Number of id	37	37	37	37
Bank fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
LINEAR COMBINATION				
SEC_HR + POST_SEC_HR		-0.0002		-0.0004

Table 9 – Robustness check: Low-risk securitization and stock price tail risk

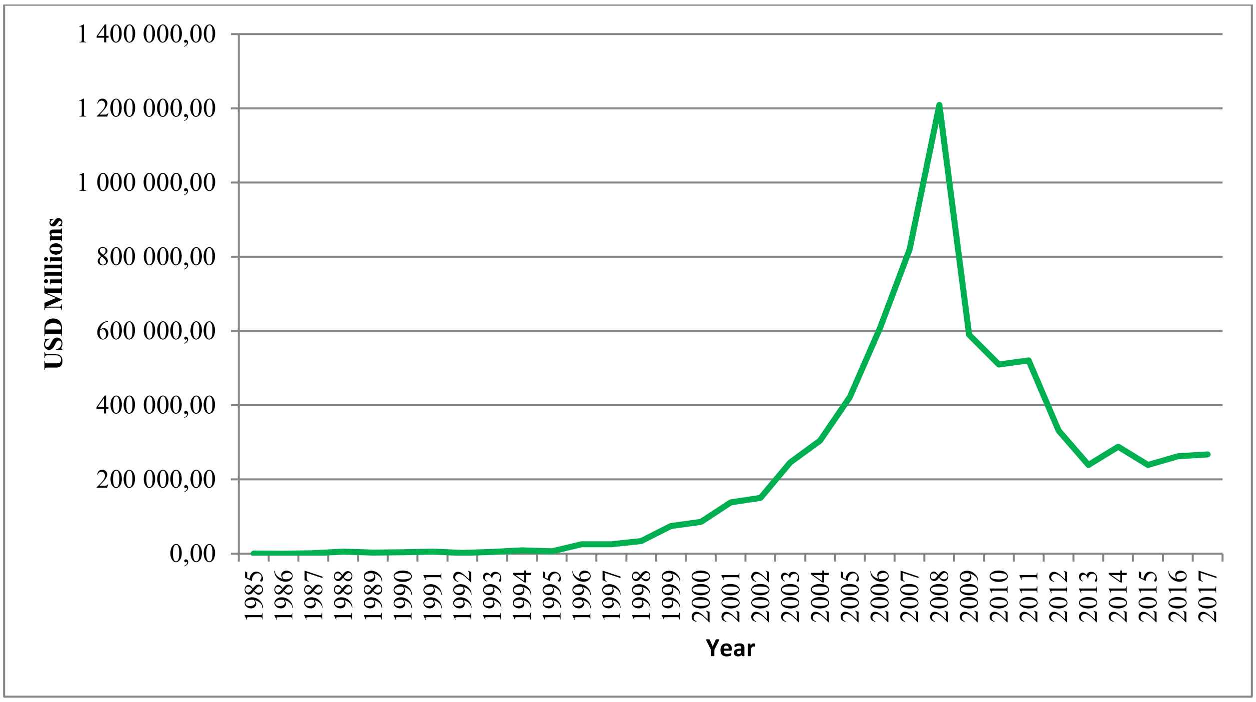
This table reports results from regressions in the form of equation (1). The dependent variable is a measure of stock price tail risk. The dependent variable is Value at Risk, one-day, 97.5% in Models 1a and 1b, and Expected Shortfall in Models 2a and 2b. The main variables of interest are the indicator variables identifying the use of low-risk securitization as defined in Table 1. All continuous variables are standardized and winsorized at the 1 and 99 percentiles. Control variables are Size, Tier 1 ratio (which are lagged one year) and inflation. Robust standard errors clustered at the country level are reported in parentheses. ***, **, * denotes that estimates are statistically significant at the 1, 5 and 10% levels.

VARIABLES	(1a) var_0975	(1b) var_0975	(2a) es_0975	(2b) es_0975
PRE_SEC_LR	0.00155	0.00248	0.00165	0.00258
	(0.00261)	(0.00290)	(0.00267)	(0.00298)
SEC_LR	-0.00910***	-0.00894***	-0.00922***	-0.00906***
	(0.00238)	(0.00225)	(0.00241)	(0.00227)
POST_SEC_LR	0.00131	0.00125	0.00128	0.00122
	(0.00245)	(0.00230)	(0.00250)	(0.00235)
$SIZE_{t-1}$	-	0.0273*	-	0.0271
		(0.0149)		(0.0153)
$TIER\ 1_{t-1}$	-	-0.00739	-	-0.00757
		(0.00627)		(0.00635)
INF_t	-	0.00142	-	0.00144
		(0.00277)		(0.00281)
Constant	0.127***	0.124***	0.130***	0.127***
	(0.0106)	(0.0120)	(0.0114)	(0.0127)
Observations	433	433	433	433
R-squared	0.697	0.704	0.695	0.702
Number of id	37	37	37	37
Bank fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
LINEAR COMBINATION				
SEC_LR + POST_SEC_LR		-0.0077***		-0.0078***

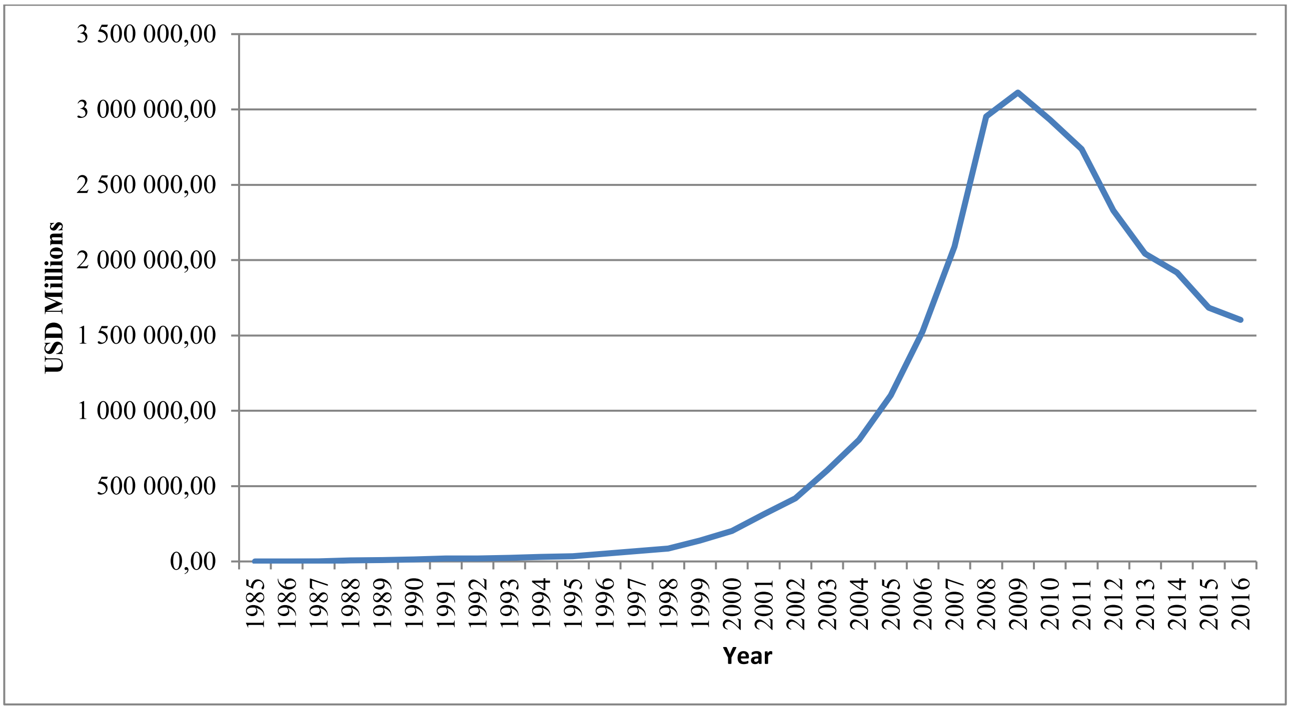
Figure 1 – European Securitization - Issuance

Panels A displays the European securitization issuances between 1985-2017. Panel B displays the outstanding securitizations in Europe during the same period. The securitizations include asset backed securities (auto, consumer, credit card loans, leases), MBS, CDOs, WBS (whole business securitizations) and SMEs (small and medium enterprise). Source: SIFMA.

Panel A - Issuance



Panel B - European Securitization - Outstanding



Source: SIFMA

Appendix 1 – Definition of Variables

This appendix reports the definition of all variables used in our empirical analysis. # means own calculations using Thomson Reuters data; + means own calculations using Datastream data; § means the source of data is World Bank WDI.

Variable	Description
Explanatory variables	
$SEC^{\#}$	Ratio of a banks' cumulative securitization volume to total assets in the current year *t*
$POST\_SEC^{\#}$	Ratio of a banks' cumulative securitization volume to total assets in *t-1*
$PRE\_SEC^{\#}$	Ratio of a banks' cumulative securitization volume to total assets in *t+1*
$SEC\_HR^{\#}$	Ratio of a banks' cumulative high-risk securitization volume in the current year *t* to total assets, when the underlying asset type is a collateralized debt obligation - CDO (high yield bonds, corporate loans, investment grade bonds, preferred stock or structured finance credit)
$POST\_SEC\_HR^{\#}$	Ratio of a banks' cumulative high-risk securitization volume done in previous year to total assets, when the underlying asset type is a collateralized debt obligation (high yield bonds, corporate loans, investment grade bonds, preferred stock or structured finance credit)
$PRE\_SEC\_HR^{\#}$	Ratio of cumulative high-risk securitization volume that banks will have the following year to total assets, while the underlying asset type is a collateralized debt obligation - CDO (high yield bonds, corporate loans, investment grade bonds, preferred stock or structured finance credit)
$SEC\_LR^{\#}$	Ratio of a banks' cumulative low-risk securitization volume in the current year *t* to total assets, when the underlying asset type is not a collateralized debt obligation – CDO
$POST\_SEC\_LR^{\#}$	Ratio of a banks' cumulative low-risk securitization volume done in the previous year to total assets, when the underlying asset type is not a collateralized debt obligation – CDO
$PRE\_SEC\_LR^{\#}$	Ratio of cumulative low-risk securitization volume that banks will have the following year to total assets, when the underlying asset type is not a collateralized debt obligation – CDO
$Size^{+}$	Ln of accounting value of the bank's total assets per year
Tier 1^{+}	Ratio of the accounting value of the bank's TIER 1 capital to risk weighted assets per year
$Inf^{\S}$	Inflation per year

Variable	Description
Dependent variables	
$CRASH\_JUMP^{+}$	Number of crashes minus number of jumps in a given year
$NCSKEW^{+}$	The negative of the third moment of bank-specific weekly returns, divided by the standard deviation cubed
$DUVOL^{+}$	Down-to-up volatility, which is the log of the ratio of the standard deviation in the crash weeks to the standard deviation in the jump weeks
VAR_0975^{+}	Value at Risk, one-day, 97.5%
ES_0975^{+}	Expected shortfall, one-day, 97.5%

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