Securitization and Crash Risk: Evidence from Large European Banks.

Abstract

The global financial crisis highlights the importance of securitization and crash risk. We analyze the relationship between securitization and crash risk in a sample of large European banks listed on the EuroStoxx 600 between 2000 and 2017. We use a dynamic panel data approach to establish a causal relationship. We test the robustness of results with different tail risk measures. Our evidence shows that crash risk declines in the year of securitization and increases the following year. This effect is driven by less complex securitization deals. The risk reduction effect is weaker in crisis periods relative to normal times. Our findings have policy implications as regulators attempt reviving European securitization markets.

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

Is there a significant link between securitization and crash risk? To date, the nature of the relation between securitization and crash risk remains an open question. This is interesting because the 2008 global financial crisis (hereafter known as GFC) drew increased attention to both securitization and crash risk. We aim to address this gap in the literature by examining whether securitization activity increases/decreases originator's crash risk. We investigate this question in a European context, since the securitization industry in the EU has struggled to return to its pre-GFC levels.

Prior to the GFC, securitization became the funding model and risk transfer method of choice for many global financial institutions (Buchanan, 2016). However, in 2008 origination and issuance of securitized products declined markedly and, in some instances, ceased altogether (Anderson, 2019). 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., 2011). Crash risk captures risk asymmetry[1] and matters because large stock price declines can diminish firm value, investor wealth and potentially induce financial

[1] Crash risk is a function of skewness.

market instability. Consequently, investors will require higher expected returns for firms with more crash risk (Harvey and Siddique, 2000).

Specifically, our paper answers the following research question: Does securitization activity decrease the originators' crash risk? We also examine whether the relationship between securitization and crash risk differs for more and less-complex securitizations. We find a reduction in crash 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 more and less complex deals, securitization transactions exhibit different effects on crash risk. In more complex securitizations, banks may securitize opaque assets in anticipation of an increase in crash risk; in less complex 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 crash risk. Finally, we also show that the crash risk reduction effect is weaker in the crisis period relative to normal times. Our findings are robust to a variety of model specifications.

The relationship between crash risk and securitization is challenging since the bank's decision to start a securitization deal is strictly endogenous (i.e., a bank decides if and when to start a securitization deal and what will be the underlying assets). There is also reverse causality (i.e., a bank starts a securitization deal based on its risk) and omitted variable issues to consider. To face these challenges, we use an identification strategy based on a dynamic panel data model, which is consistent with recent literature (Gopalan et al., 2016; Fiordelisi et al., 2019) that enables us to address the reverse causality problem.

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). At the individual stock level information transparency is related to less crash risk. As observed by Habib et al. (2018), some stocks are potentially more prone to crash due to the fundamental (opaque) nature of their operations: in the banking industry crash risk has been related to earnings management (Cohen et al., 2014) and the use of financial derivatives (Dewally and Shao; 2013; Trapp and Weiß; 2016). 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., 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).

Third, our paper focuses on European banking. As outlined by Kara et al. (2019), even though Europe is the second largest securitization market worldwide, there is a lack of evidence on the impact of securitization on European banks' behavior. Most securitization papers have focused on the US (e.g., Casu et al., 2013; Loutskina and Strahan, 2009; Loutskina, 2011; Chava and Purnanandam, 2011; Dell'Ariccia et al., 2012; Gorton and Metrick, 2012; 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; 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 questions. 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 research questions

2.1 Securitization Background and Literature Review

Securitization radically transformed the global financial landscape. Prior to the GFC, securitization was a popular method of financing the mortgage and consumer credit markets. After the GFC, a stigma surrounded securitization and market recovery was slow. For example, as Figure One and Figure Two indicate, the European securitization market has exhibited a slow recovery post-GFC. The overall amount is still very low compared with pre-GFC levels, which approximated €450 billion (AFME, 2018).

[INSERT FIGURE ONE ABOUT HERE]

[INSERT FIGURE TWO ABOUT HERE]

European securitization issuance has declined partly because of more intensive regulatory reforms[2] post-GFC, which has curbed higher risk activities. Over time, European regulators have taken a more supportive view towards securitization[3]. As part of its quantitative easing measures, the European Central Bank bought asset backed securities. In 2015, 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)[4,5]. As bank lending became more constrained post-GFC, securitization has the potential to boost credit and growth.

The benefits of securitization 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 (Schwartz, 2009; Fabozzi, 2005; Loutskina and Strahan, 2007).

However, there are also potential drawbacks associated with the securitization process (Schwartz, 2009; Parlour and Plantin, 2008). 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 scrutinize and monitor borrowers due to the greater distance between the borrower and those who finally bear the default risk (Piskorski, Seru and Vig, 2012). Parlour and Plantin (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

[2] 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.
[3] Regulating European securitizations after the crisis, Thomas Harde, FTimes. July 30, 2018.
[4] Regulating European securitizations after the crisis, Thomas Harde, FTimes. July 30, 2018.
[5] This new amended regulation did not appear until early 2019.

diversifications more easily (Instefjord, 2005; Wagner, 2007). On the other hand, banks may also become riskier based on whether they use the funding obtained from securitization to grant riskier loans, keep the riskiest tranche in a securitization, and/or must (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 literature studying the impact of securitization on bank risk can be divided into "securitization-stability" and "securitization fragility" (Arif (2020)). In the remainder of this section, we focus on empirical studies and show that there is a strong heterogeneity of conclusions irrespective of the analyzed measure of bank 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; Fiordelisi et al., 2014; Casu et al., 2013; Michalak and Uhde, 2012; Affinito and Tagliaferri, 2010; Franke and Krahnen, 2006). 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). 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).

A second stream of literature focuses on systematic risk. Specifically, various papers show that banks display higher betas after securitization deals (Battaglia et al., 2014, Nijiskens and Wagner, 2011; Michalak and Uhde, 2010) 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 et al. (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 increases 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).

A recent paper by Anderson (2019) focuses on ambiguity in securitization markets, due to the high complexity of the ABS and CDOs, including many underlying assets with complicated default probabilities and correlations. The proposed theoretical model shows that ambiguity aversion can lead to market freezes and fire sales more intensively and faster than fundamental shocks (such as changes in risk or a deterioration of expected value). This suggests the relevance of opacity and complexity in investors' perceptions, linking the securitization literature to the one devoted to crash risk.

2.2 Crash Risk Literature Review

The second strand of literature focuses on the idea that opaque assets are related to stock price crash risk, which is the likelihood of extreme bad firm-specific returns. As outlined in previous studies (e.g., Jin and Myers, 2006), managers tend to withhold bad news for as long as possible, to safeguard their job and protect their compensation (Kothari et al., 2009). 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. 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). 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., 2018).

With reference to the banking literature, Cohen et al. (2014) provide evidence that earnings management and financial statements opacity increase crash risk in banks as in other industries. However, earnings management has a small predictive power for downside risk during normal times, which increases significantly during crisis periods. Dewally and Shao (2013) measure the opacity of banks' operations with the use of interest rate and foreign exchange financial derivatives, finding a positive relationship with crash risk. To the best of our knowledge, the only paper relating equity tail risk to securitization is Trapp and Weiß (2016). However, our paper is significantly different, for at least three reasons: first, they only consider the 2007-2009 period of the GFC, focusing on US banks, while we cover a much longer interval (2000-2017) considering European banks. Second, they use two indicators of tail risk - the Dynamic Marginal Expected Shortfall and the Conditional Value at Risk - that measure, respectively, the bank's tendency to register heavy losses when the market plummets or the individual bank's contribution to the whole system's tail risk. These measures, often used as indicators of systemic rather than crash risk, are strongly different from the ones adopted in this paper (described in next sections), which are based on extreme negative events observed in the far-left tail of the bank-specific return distribution. Consequently, the focus is on bank-specific features rather than on co-movement with the market. Finally, we use a different approach to deal with endogeneity, based on a dynamic panel model rather than to the use of lagged independent variables.

2.3 Theoretical background and research question

Overall, the relationship between securitization activity and crash risk remains an open question. There is also a dearth of papers focusing on tail risk measures (or crash risk and expected shortfall measures); none provide causal evidence that securitization either decreases or increases crash 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, despite the evidence on the direct link between opacity and crash risk. As outlined by Jones et al. (2013), opacity in the banking industry may arise from different sources, including incomplete disclosure and fundamental complexity of business that makes accurate valuation nearly impossible. In their empirical analysis, based on a sample of listed US banks and financial holding companies over a pre-crisis period (2000–2006), they identify main opaque assets with commercial loans, residential loans, and typical securitization products, such as asset and mortgage-based securities. Using a more recent sample (2005-2014), including banks based in Europe, Kosmidou et al. (2017) also find a relationship between crash risk and loan opacity. How does this apply to our case? On the one hand, there are reasons to expect that recourse to securitization is associated with higher crash risk. Securitization maybe a quite opaque process itself; originating banks may hold in their portfolio some asset and mortgage backed securities deriving from securitization, which are sometimes difficult to evaluate. And, most importantly, banks may use liquid funds obtained by securitization to lend more to risky borrowers and retain riskier loans. On the other hand, a competing hypothesis is that securitization is associated with lower crash risk. Following previous studies, the most opaque assets in the banking business are loans, especially those that are granted to counterparties without a rating and difficult to evaluate (e.g., commercial and residential loans). Using securitization banks are able to sell (risky) loans, obtain liquid funds, and then reduce the opaqueness of their balance sheet. Which effect is prevailing remains an empirical question and is the focus of this paper: Does securitization activity decrease the originators' crash risk?

We also test if the relationship between securitization and crash risk differs depending on the underlying assets of securitization deal. More specifically, we identify a subsample of less complex securitizations (i.e., loans with a high degree of standardization, collateralization and granularity) and more complex securitizations[6] (i.e., high number of complex loan arrangements, which are typically difficult to evaluate for potential investors and, hence, are perceived as

[6] Farruggio and Uhde (2015)

riskier by them). This leads to an additional test, where we examine whether the relationship between securitization and crash risk differs for more and less complex securitizations?

We define more complex securitizations as 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); less complex securitizations: transactions when the underlying asset type is not a CDO. This distinction is consistently with the additional complexity of CDOs (see also Anderson 2019).

3. Empirical Methodology

Our identification strategy addresses the issue of potential endogeneity in establishing a causal relationship between securitization and the downside 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 crash risk).

We follow some recent papers proposing a dynamic panel data approach to address the endogeneity issue (Gopalan, et al., 2016; Fiordelisi et al., 2019). The adopted approach is very similar to Fiordelisi et al. (2019), using a dynamic panel estimation to assess the impact of issuing contingent convertible bonds on several indicators of bank crash risk. 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[7]. 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 measures the effect of securitization on bank crash risk in the following year. 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 crash 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), both in lags (at the time t-1). At the country level, we consider the dynamic of prices (INFLATION) to control for both economic and financial conditions[8]. We also 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 a sample of European banks, we also consider the Eurozone sovereign debt crisis, which was in its most acute phase until 2013[9]. Finally, to alleviate a potential missing (or

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[7] 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. Obviously, these leads and lags may also be equal to zero.

[8] We also tried to include other controls at the bank level, such as the GDP growth rate and the level of concentration in the banking industry measured by the HHI index, and results remains unaltered.

[9] We thank an anonymous referee for suggesting the inclusion of a crisis dummy in all our models.

omitted) variables problem, we also include in our model bank- and year-fixed effects (respectively A_i and B_t). We calculate robust standard errors clustered at the country level.

Following recent studies, we consider as dependent variables 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[10]). From this model, we obtain bank-specific returns as the residual from regression (2)[11].

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*).

It is very important to stress that crashes are not effective realizations, but represent bank-specific extreme price movements over and above those due to common risk factors. Hence, each crash is defined from an idiosyncratic perspective and identifies an extreme event

[10] The use of a general, rather than a banking industry market index, is consistent with past literature. For example, both Dewally and Shao (2013) and Callen and Fang (2015) use the CRSP value-weighted market index return.
[11] Following Hutton et al. (2009), we adopt a log transformation of residuals from equation (2) which are highly skewed. Specifically, we use bank-specific returns given by the log of one plus the residual.

with respect to the bank-specific distribution of returns, which are those not explained by general market movements.

Following Hutton et al. (2009) and Callen and Fang (2015), we also consider the negative conditional skewness (NCSKEW), which is calculated as:

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

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:

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

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. A higher value for DUVOL corresponds to a stock being more ''crash prone.''

As a second step, we run a model considering the potential impact of the global financial crisis. 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 crash 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[12]. 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 a homogenous sample, not biased by differences in accounting standards, loan portfolio management techniques and business policies. The sample is based on 11 European countries: Austria, Belgium, Denmark, Germany, France, Italy, Netherlands, Spain, Sweden, Switzerland, and United Kingdom[13].

Our sample covers the period from 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

[12]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.

[13] Although our sample is a quite small, it covers all countries (Austria, Belgium, Denmark, Germany, France, Italy, Netherlands, Spain, Sweden, Switzerland, and United Kingdom) represented by percentages spanning from 5.54% (i.e. Austria) to 12.93% (i.e. Sweden).

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 37 listed banks for a total number of 433 bank-year observations. All our sample securitizing banks are frequent issuers, with the exception of Nordea and Swed bank for which only one security transaction is recorded over the entire investigation period. If a bank securitizes several 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_MC and SEC_LC. The first one, SEC, is the ratio of a banks' cumulative securitization volume to total assets, while SEC_MC and SEC_LC refer to the complexity of the underlying assets. Specifically, following Anderson (2019), 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 less complex securitizations when the underlying asset type is not a CDO.

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

Table 1, Panel A 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) the average value 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. Panel B details the sample classified by country. The UK (16.4%), followed by Spain (13.16%) and Sweden (12.93%) account for the most securitizations.

[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). 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 less complex securitizations (SEC_LC). However, they all have a positive correlation with more complex securitizations (SEC_MC). Table 2 appears to provide some preliminary evidence related to our research questions. However, we consider this evidence preliminary 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 crash 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 always 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 12.8% and 12.7% (respectively in Models 1a and 1b); to a decrease of *NCSKEW* of about 9.56% and 9.69% (respectively in Models 2a and 2b), and to a decrease of *DUVOL* of about 5.54% and 5.71% (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 are consistent with those obtained from previous studies, finding a reduction in the crash risk of the banks in the year of the securitization (negative contemporaneous effect), but an increase in the crash 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 crash 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, 2006; 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 (Instefjord, 2005).

Second, we distinguish the underlying asset portfolio of securitization transactions, running model in equation (1), respectively, for more and less-complex securitizations. For more-complex 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_MC* is positive and statistically significant at the 5% confidence level for crashes minus jumps (*CRASH_JUMP*), providing some evidence that banks may securitize opaque assets in anticipation of an increase in crash risk. For all other risk measures, there are no significant results at the 10% confidence level or less.

[INSERT TABLE FOUR ABOUT HERE]

Finally, we run the model in equation (1) for less-complex securitizations and the results are shown in Table 5. Our findings are very similar to the general model in Table 3. More specifically, the less-complex subsample confirms the results of the overall sample: there is evidence of a contemporaneous risk-reduction effect of securitization and a post-event increase in crash risk. However, in the case of less-complex 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 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 crash risk reduction effect, followed by an increase in crash risk. Overall, this leads to a weak crash risk reduction effect, which is statistically significant at the 10% confidence level only for crashes minus jumps (*CRASH_JUMP*). During crisis periods, we must also consider 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 cannot reject the null hypothesis that the effect of securitization on crash risk was null during the crisis period. Overall, we do not find any evidence that securitization, during crisis periods, reduces crash risk.

[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 still consider the stock price dynamic of each originating bank but taking into account the most common indicators of tail risk i.e., Value at Risk (*VaR*) and Expected Shortfall (*ES*) rather than crash risk. For both indicators, we use a historical simulation approach, with a confidence level of 97.5% and a one-week holding period, using one year of stock weekly returns[14].

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 9.60‰ and 9.35‰ respectively in Models 1a and 1b, and to a decrease of the ES of about 9.70‰ and 9.45‰ 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]

[14] We do not use a 99% confidence interval because we have weekly returns over one year of data, and then about 50 observations a year. As a consequence, using a tail of 1% would lead to cut observations in a way that we obtain the same value for VAR and ES.

Finally, as a further robustness check, we adopt a GMM framework, in which lagged differences of the dependent variables and our main macroeconomic indicator are used to generate the instruments. Results are shown in Table 10 for our basic specification, using the total volume of securitization. When statistically significant at the 10% confidence level or less, results confirm our main finding of a negative relationship between the use of securitization and the level of risk perceived by investors[15].

[INSERT TABLE TEN ABOUT HERE]

7. Conclusions

Our paper examines whether securitizing banks tend to be more prone to crash risk. By analyzing a sample drawn on European commercial listed banks included in the Euro Stoxx 600 index and covering all securitization activity during the period 2000-2017, we provide novel evidence that there is a reduction in bank crash risk during the year a bank securitizes (a negative contemporaneous effect), and an increase in risk after the securitization issuance (positive post-securitization effect). We also find that, in more complex securitizations, banks may securitize opaque assets in anticipation of an increase in crash risk, pointing to a reverse causality problem. In less-complex securitizations, we show a contemporaneous risk-reduction effect of securitization and a post-event increasing crash risk. Finally, we also find 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. First, we show that securitization enable banks to immediately reduce crash risk and, thus, a more efficient securitization market is beneficial for bank stability.

[15] Distinguishing between high and low risk securitization, results show that the negative relationship between securitization and risk is weaker for the former.

Second, the negative effect found in the year after the securitization show that it is important to assess how banks employ financial resources made available by securitization. Finally, our results support that disclosure requirements should be enhanced to let investors to capture whether banks securitize opaque assets in anticipation of an increase in crash risk.

Table 1 – Descriptive Statistics

In Panel A we report the mean, standard deviation, minimum and maximum of the variables used in our empirical analysis. In Panel B, we categorize the observations according to country. In the sample, Austria (AT), Belgium (BE), Switzerland (CH), Germany (DE), Denmark (DK), Spain (ES), France (FR), UK (GB), Italy (IT), Netherlands (NL), and Sweden (SE) are represented.

Panel A – Descriptive statistics

Variables	Obs	Mean	Std	Min	Max
SEC	433	0.01395	0.02843	0.00000	0.24499
SEC_MC	433	0.00156	0.00463	0.00000	0.04610
SEC_LC	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

Panel B – Observations by country

Country	*Freq.*	*Percent*	*Cum.*
AT	24	5.54	5.54
BE	15	3.46	9.01
CH	35	8.08	17.09
DE	25	5.77	22.86
DK	45	10.39	33.26
ES	57	13.16	46.42
FR	48	11.09	57.51
GB	71	16.4	73.9
IT	45	10.39	84.3
NL	12	2.77	87.07
SE	56	12.93	100
Total	433	100	

Table 2 – Correlation matrix

	Sec	Sec_mc	Sec_lc	Crash_jump	Ncskew	Duvol	Var_0975	Es_0975	Size	Tier1_	Inf
SEC	1.0000										
SEC_MC	0.7826	1.0000									
SEC_LC	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), inflation and crisis. 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	0.0598	0.0709	0.0200	0.0258	0.00449	0.00967
	(0.0405)	(0.0426)	(0.0328)	(0.0329)	(0.0341)	(0.0340)
SEC	-0.128**	-0.127**	-0.0956**	-0.0969**	-0.0554	-0.0571*
	(0.0432)	(0.0425)	(0.0403)	(0.0385)	(0.0310)	(0.0294)
POST_SEC	0.0425	0.0433	0.0444	0.0463	0.0197	0.0220
	(0.0594)	(0.0619)	(0.0490)	(0.0489)	(0.0300)	(0.0284)
$SIZE_{t-1}$		0.281*		0.108		0.0826
		(0.144)		(0.139)		(0.0975)
$TIER\ 1_{t-1}$		-0.0784**		-0.0483		-0.0507
		(0.0335)		(0.0747)		(0.0396)
INF_t		0.0408		0.0395		0.0437
		(0.0336)		(0.0407)		(0.0347)
CRISIS		-0.0497		-0.0685		0.0208
		(0.283)		(0.316)		(0.190)
Constant	-0.186	-0.0240	-0.0999	0.0339	-0.0346	-0.00858
	(0.106)	(0.223)	(0.159)	(0.286)	(0.101)	(0.194)
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		-0.084*		-0.0506		-0.0351

Table 4 – More complex 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 more-complex 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), inflation and crisis. 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_MC	0.0535**	0.0573**	0.0106	0.0124	0.00601	0.00748
	(0.0236)	(0.0235)	(0.0192)	(0.0187)	(0.0216)	(0.0235)
SEC_MC	-0.0503	-0.0454	-0.0163	-0.0140	-0.0150	-0.0132
	(0.0405)	(0.0393)	(0.0358)	(0.0353)	(0.0235)	(0.0236)
POST_SEC_MC	0.00241	0.000483	0.0112	0.0104	0.0240	0.0235
	(0.0312)	(0.0324)	(0.0350)	(0.0362)	(0.0200)	(0.0208)
$SIZE_{t-1}$		0.298**		0.132		0.101
		(0.123)		(0.139)		(0.0931)
$TIER\ 1_{t-1}$		-0.0749*		-0.0470		-0.0486
		(0.0346)		(0.0724)		(0.0389)
INF_t		0.0386		0.0384		0.0439
		(0.0392)		(0.0432)		(0.0382)
CRISIS		-0.0584		-0.0714		0.0220
		(0.282)		(0.313)		(0.187)
Constant	-0.182	-0.0272	-0.0929	0.0298	-0.0237	-0.0113
	(0.102)	(0.223)	(0.156)	(0.287)	(0.102)	(0.193)
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_MC + POST_SEC_MC		-0.0450		-0.0036		0.0103

Table 5 – Less Complex 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 less-complex 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), inflation and crisis. 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_LC	0.0448	0.0566	0.0155	0.0216	0.00131	0.00678
	(0.0443)	(0.0475)	(0.0347)	(0.0355)	(0.0348)	(0.0345)
SEC_LC	-0.122**	-0.123**	-0.101**	-0.102**	-0.0558*	-0.0580*
	(0.0422)	(0.0418)	(0.0398)	(0.0388)	(0.0307)	(0.0298)
POST_SEC_LC	0.0424	0.0440	0.0442	0.0466	0.0120	0.0147
	(0.0592)	(0.0617)	(0.0467)	(0.0460)	(0.0296)	(0.0273)
$SIZE_{t-1}$		0.276*		0.105		0.0802
		(0.145)		(0.139)		(0.0980)
$TIER\ 1_{t-1}$		-0.0794**		-0.0490		-0.0514
		(0.0336)		(0.0755)		(0.0397)
INF_t		0.0404		0.0394		0.0433
		(0.0323)		(0.0400)		(0.0341)
CRISIS		-0.0500		-0.0690		0.0201
		(0.283)		(0.316)		(0.190)
Constant	-0.185	-0.0227	-0.102	0.0343	-0.0377	-0.00890
	(0.107)	(0.222)	(0.158)	(0.286)	(0.101)	(0.194)
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_LC + POST_SEC_LC		-0.0786*		-0.0556		-0.0433*

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), inflation and crisis. 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	0.0827	0.0932	0.0457	0.0509	0.00986	0.0152
	(0.0649)	(0.0663)	(0.0497)	(0.0494)	(0.0432)	(0.0429)
SEC	-0.232**	-0.234**	-0.227**	-0.230**	-0.133*	-0.136*
	(0.0895)	(0.0915)	(0.0766)	(0.0774)	(0.0621)	(0.0624)
POST_SEC	0.138*	0.143**	0.169**	0.173***	0.102*	0.106**
	(0.0654)	(0.0641)	(0.0548)	(0.0525)	(0.0473)	(0.0438)
$SIZE_{t-1}$		0.289*		0.105		0.106
		(0.136)		(0.130)		(0.0962)
$TIER\ 1_{t-1}$		-0.0771*		-0.0492		-0.0483
		(0.0347)		(0.0756)		(0.0410)
INF_t		0.0422		0.0429		0.0448
		(0.0315)		(0.0395)		(0.0331)
CRISIS		-0.0571		-0.0713		0.0113
		(0.283)		(0.310)		(0.191)
*PRE_SEC*CRISIS*	-0.118	-0.112	-0.114	-0.106	0.00409	0.0122
	(0.177)	(0.187)	(0.136)	(0.145)	(0.0496)	(0.0520)
*SEC*CRISIS*	0.298	0.282	0.363	0.361	0.106	0.104
	(0.394)	(0.378)	(0.290)	(0.284)	(0.145)	(0.139)
*POST_SEC*CRISIS*	-0.170	-0.181	-0.222**	-0.226**	-0.163**	-0.167**
	(0.103)	(0.109)	(0.0933)	(0.0972)	(0.0655)	(0.0669)
Constant	-0.179	-0.0245	-0.0900	0.0396	-0.0272	-0.0150
	(0.107)	(0.218)	(0.158)	(0.282)	(0.101)	(0.196)
Observations	433	433	433	433	433	433
Bank fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
LINEAR COMBINATION						
a) SEC+POST_SEC		-0.0912*		- 0.0566		-0.0294
*b) SEC*CRISIS+POST_SEC*CRISIS*		0.1005		0.1350		-0.0630
c) A+B		0.0093		0.0784		-0.0925

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-week, 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), inflation and crisis. 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	0.00134	0.00221	0.00143	0.00230
	(0.00262)	(0.00295)	(0.00268)	(0.00302)
SEC	-0.00960**	-0.00935**	-0.00970**	-0.00945**
	(0.00313)	(0.00300)	(0.00316)	(0.00303)
POST_SEC	0.00272	0.00259	0.00266	
	(0.00274)	(0.00267)	(0.00279)	
$SIZE_{t-1}$		0.0265*		0.0263
		(0.0145)		(0.0149)
$TIER\ 1_{t-1}$		-0.00718		-0.00736
		(0.00615)		(0.00623)
INF_t		0.00144		0.00146
		(0.00279)		(0.00284)
CRISIS		-0.0214**		-0.0223**
		(0.00693)		(0.00707)
Constant	0.127***	0.106***	0.131***	0.108***
	(0.0106)	(0.00665)	(0.0115)	(0.00673)
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		-0.0068**		- 0.0069**

Table 8 – Robustness check: More-complex 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-week, 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 more-complex 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), inflation and crisis. 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_MC	-0.00187*	-0.00159	-0.00188*	-0.00161
	(0.000949)	(0.00110)	(0.000964)	(0.00112)
SEC_MC	-0.00369*	-0.00323*	-0.00368*	-0.00322*
	(0.00172)	(0.00159)	(0.00173)	(0.00160)
POST_SEC_MC	0.00322	0.00300	0.00309	0.00288
	(0.00194)	(0.00194)	(0.00194)	(0.00193)
$SIZE_{t-1}$		0.0267*		0.0265*
		(0.0138)		(0.0142)
$TIER\ 1_{t-1}$		-0.00712		-0.00730
		(0.00615)		(0.00624)
INF_t		0.00135		0.00137
		(0.00289)		(0.00293)
CRISIS		-0.0212**		-0.0221***
		(0.00680)		(0.00696)
Constant	0.129***	0.106***	0.133***	0.108***
	(0.0107)	(0.00650)	(0.0115)	(0.00659)
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_MC + *POST_SEC_MC*		-0.0002		-0.0003

Table 9 – Robustness check: Less-complex 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-week, 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 less-complex 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), inflation and crisis. 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_LC	0.00160	0.00256	0.00170	0.00266
	(0.00269)	(0.00300)	(0.00275)	(0.00307)
SEC_LC	-0.00939***	-0.00922***	-0.00951***	-0.00934***
	(0.00246)	(0.00232)	(0.00248)	(0.00235)
POST_SEC_LC	0.00135	0.00129	0.00132	0.00126
	(0.00252)	(0.00237)	(0.00258)	(0.00243)
$SIZE_{t-1}$		0.0268*		0.0266
		(0.0146)		(0.0150)
$TIER\ 1_{t-1}$		-0.00726		-0.00744
		(0.00618)		(0.00626)
INF_t		0.00142		0.00144
		(0.00277)		(0.00281)
CRISIS		-0.0214**		-0.0223***
		(0.00688)		(0.00702)
Constant	0.127***	0.106***	0.130***	0.108***
	(0.0106)	(0.00661)	(0.0114)	(0.00669)
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_LC + POST_SEC_LC		-0.0079***		- 0.0081***

Table 10 – Robustness check: GMM estimation

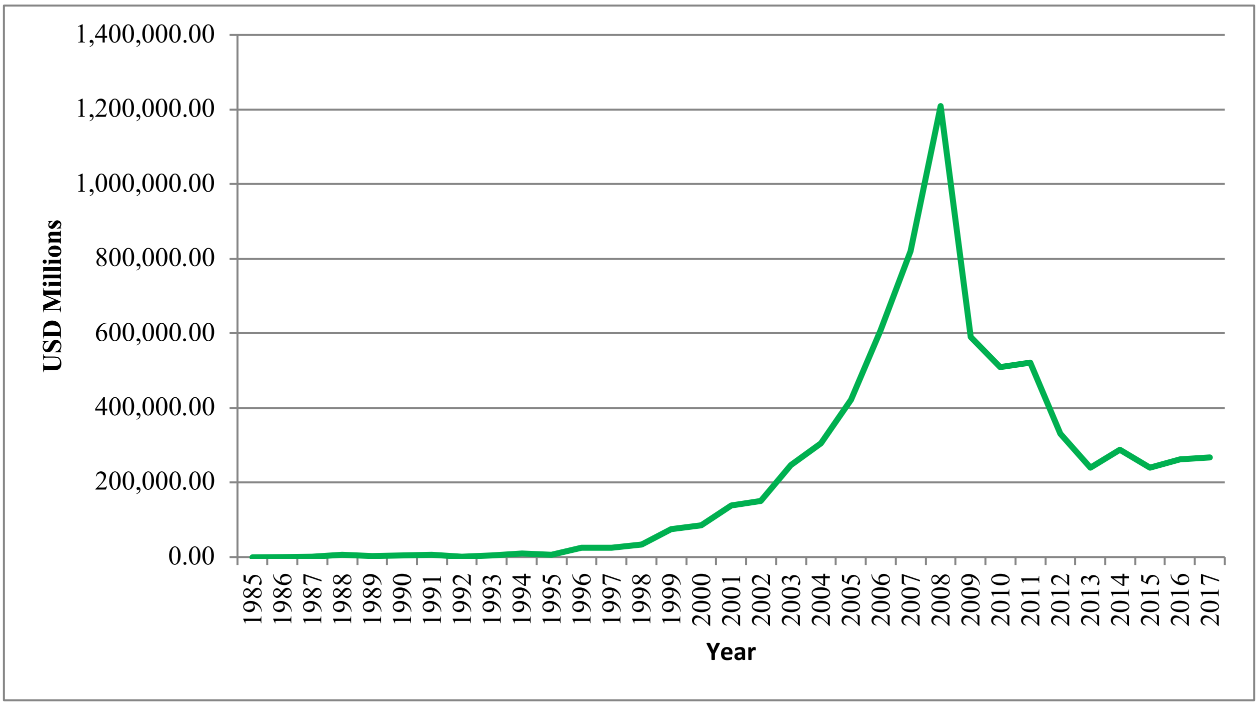
This table reports results from a GMM estimation including the first lag of each dependent variable (a measure of stock price tail risk). The main variables of interest are the indicator variables identifying the use of securitization as defined in Table 1. All continuous variables are standardized and winsorized at the 1 and 99 percentiles. Control variables are Size, Tier 1 ratio (which are lagged one year), inflation and crisis. Robust standard errors are reported in parentheses. ***, **, * denotes that estimates are statistically significant at the 1, 5 and 10% levels.

VARIABLES	(1) crash_jump	(2) ncskew	(3) duvol	(4) var_0975	(5) es_0975
SEC	0.0352	-0.2067	-0.2166	-0.0973***	-0.0970***
	(0.1468)	(0.1682)	(0.2301)	(0.0355)	(0.0361)
$SIZE_{t-1}$	0.4636***	0.4418***	0.2605***	0.0016	0.0007
	(0.0979)	(0.1212)	(0.0642)	(0.0116)	(0.0121)
$TIER\ 1_{t-1}$	0.1770	-0.0616	-0.1533	0.0024	0.0025
	(0.1971)	(0.2093)	(0.1893)	(0.0156)	(0.0157)
INF_t	1.1275	1.1482*	0.7985	0.2028***	0.2053***
	(0.8643)	(0.6471)	(0.5603)	(0.0498)	(0.0513)
CRISIS	0.1323	0.1014	-0.0102	-0.0813***	-0.0824***
	(0.2097)	(0.2015)	(0.1511)	(0.0220)	(0.0226)
$CRASH\_JUMP_{t-1}$	-0.4597**				
	(0.2049)				
$NCSKEW_{t-1}$		-0.3178**			
		(0.1447)			
$DUVOL_{t-1}$			-0.3627		
			(0.2279)		
VAR_0975_{t-1}				-0.2835**	
				(0.1203)	
ES_0975_{t-1}					-0.2866**
					(0.1213)
Observations	378	378	378	378	378
Number of id	34	34	34	34	34
Sargan Hansen test	23.10	25.63	23.00	28.01	28.03
p-value	0.339	0.221	0.344	0.140	0.139

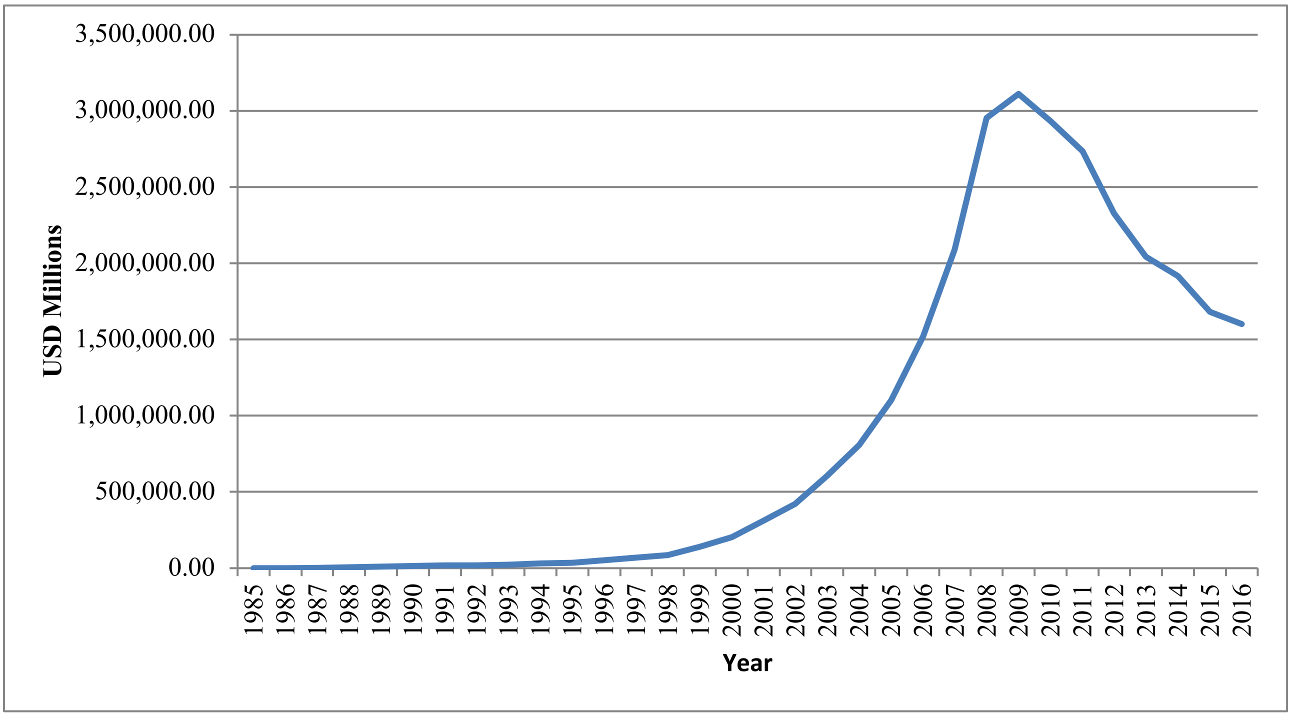
Figure 1 – European Securitization - Issuance

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). Both charts cover major regulatory interventions such as Basel III (2009), Capital Requirements Directives (CRD) II (2011), CRD III (2010), CRD IV (2013) and Simple, Transparent and Standardized (STS) securitizations (set out in 2017, but still in progress). 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_MC#	Ratio of a banks' cumulative more-complex 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_MC#	Ratio of a banks' cumulative more-complex 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_MC#	Ratio of cumulative more-complex 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_LC#	Ratio of a banks' cumulative less-complex securitization volume in the current year *t* to total assets, when the underlying asset type is not a collateralized debt obligation – CDO
POST_SEC_LC#	Ratio of a banks' cumulative less-complex securitization volume done in the previous year to total assets, when the underlying asset type is not a collateralized debt obligation – CDO
PRE_SEC_LC#	Ratio of cumulative less-complex 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§	Inflation per year

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-week, 97.5%
ES_0975+	Expected shortfall, one-week, 97.5%

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Securitization and Crash Risk: Evidence from Large European Banks.

Abstract

The global financial crisis highlights the importance of securitization and crash risk. We analyze the relationship between securitization and crash risk in a sample of large European banks listed on the EuroStoxx 600 between 2000 and 2017. We use a dynamic panel data approach to establish a causal relationship. We test the robustness of results with different tail risk measures. Our evidence shows that crash risk declines in the year of securitization and increases the following year. This effect is driven by less complex securitization deals. The risk reduction effect is weaker in crisis periods relative to normal times. Our findings have policy implications as regulators attempt reviving European securitization markets.

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

Is there a significant link between securitization and crash risk? To date, the nature of the relation between securitization and crash risk remains an open question. This is interesting because the 2008 global financial crisis (hereafter known as GFC) drew increased attention to both securitization and crash risk. We aim to address this gap in the literature by examining whether securitization activity increases/decreases originator's crash risk. We investigate this question in a European context, since the securitization industry in the EU has struggled to return to its pre-GFC levels.

Prior to the GFC, securitization became the funding model and risk transfer method of choice for many global financial institutions (Buchanan, 2016). However, in 2008 origination and issuance of securitized products declined markedly and, in some instances, ceased altogether (Anderson, 2019). 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., 2011). Crash risk captures risk asymmetry[1] and matters because large stock price declines can diminish firm value, investor wealth and potentially induce financial

[1] Crash risk is a function of skewness.

market instability. Consequently, investors will require higher expected returns for firms with more crash risk (Harvey and Siddique, 2000).

Specifically, our paper answers the following research question: Does securitization activity decrease the originators' crash risk? We also examine whether the relationship between securitization and crash risk differs for more and less-complex securitizations. We find a reduction in crash 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 more and less complex deals, securitization transactions exhibit different effects on crash risk. In more complex securitizations, banks may securitize opaque assets in anticipation of an increase in crash risk; in less complex 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 crash risk. Finally, we also show that the crash risk reduction effect is weaker in the crisis period relative to normal times. Our findings are robust to a variety of model specifications.

The relationship between crash risk and securitization is challenging since the bank's decision to start a securitization deal is strictly endogenous (i.e., a bank decides if and when to start a securitization deal and what will be the underlying assets). There is also reverse causality (i.e., a bank starts a securitization deal based on its risk) and omitted variable issues to consider. To face these challenges, we use an identification strategy based on a dynamic panel data model, which is consistent with recent literature (Gopalan et al., 2016; Fiordelisi et al., 2019) that enables us to address the reverse causality problem.

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). At the individual stock level information transparency is related to less crash risk. As observed by Habib et al. (2018), some stocks are potentially more prone to crash due to the fundamental (opaque) nature of their operations: in the banking industry crash risk has been related to earnings management (Cohen et al., 2014) and the use of financial derivatives (Dewally and Shao; 2013; Trapp and Weiß; 2016). 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., 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).

Third, our paper focuses on European banking. As outlined by Kara et al. (2019), even though Europe is the second largest securitization market worldwide, there is a lack of evidence on the impact of securitization on European banks' behavior. Most securitization papers have focused on the US (e.g., Casu et al., 2013; Loutskina and Strahan, 2009; Loutskina, 2011; Chava and Purnanandam, 2011; Dell'Ariccia et al., 2012; Gorton and Metrick, 2012; 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; 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 questions. 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 research questions

2.1 Securitization Background and Literature Review

Securitization radically transformed the global financial landscape. Prior to the GFC, securitization was a popular method of financing the mortgage and consumer credit markets. After the GFC, a stigma surrounded securitization and market recovery was slow. For example, as Figure One and Figure Two indicate, the European securitization market has exhibited a slow recovery post-GFC. The overall amount is still very low compared with pre-GFC levels, which approximated €450 billion (AFME, 2018).

[INSERT FIGURE ONE ABOUT HERE]

[INSERT FIGURE TWO ABOUT HERE]

European securitization issuance has declined partly because of more intensive regulatory reforms[2] post-GFC, which has curbed higher risk activities. Over time, European regulators have taken a more supportive view towards securitization[3]. As part of its quantitative easing measures, the European Central Bank bought asset backed securities. In 2015, 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)[4,5]. As bank lending became more constrained post-GFC, securitization has the potential to boost credit and growth.

The benefits of securitization 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 (Schwartz, 2009; Fabozzi, 2005; Loutskina and Strahan, 2007).

However, there are also potential drawbacks associated with the securitization process (Schwartz, 2009; Parlour and Plantin, 2008). 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 scrutinize and monitor borrowers due to the greater distance between the borrower and those who finally bear the default risk (Piskorski, Seru and Vig, 2012). Parlour and Plantin (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

[2] 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.
[3] Regulating European securitizations after the crisis, Thomas Harde, FTimes. July 30, 2018.
[4] Regulating European securitizations after the crisis, Thomas Harde, FTimes. July 30, 2018.
[5] This new amended regulation did not appear until early 2019.

diversifications more easily (Instefjord, 2005; Wagner, 2007). On the other hand, banks may also become riskier based on whether they use the funding obtained from securitization to grant riskier loans, keep the riskiest tranche in a securitization, and/or must (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 literature studying the impact of securitization on bank risk can be divided into “securitization-stability” and “securitization fragility” (Arif (2020)). In the remainder of this section, we focus on empirical studies and show that there is a strong heterogeneity of conclusions irrespective of the analyzed measure of bank 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; Fiordelisi et al., 2014; Casu et al., 2013; Michalak and Uhde, 2012; Affinito and Tagliaferri, 2010; Franke and Krahnen, 2006). 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). 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).

A second stream of literature focuses on systematic risk. Specifically, various papers show that banks display higher betas after securitization deals (Battaglia et al., 2014, Nijiskens and Wagner, 2011; Michalak and Uhde, 2010) 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 et al. (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 increases 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).

A recent paper by Anderson (2019) focuses on ambiguity in securitization markets, due to the high complexity of the ABS and CDOs, including many underlying assets with complicated default probabilities and correlations. The proposed theoretical model shows that ambiguity aversion can lead to market freezes and fire sales more intensively and faster than fundamental shocks (such as changes in risk or a deterioration of expected value). This suggests the relevance of opacity and complexity in investors' perceptions, linking the securitization literature to the one devoted to crash risk.

2.2 Crash Risk Literature Review

The second strand of literature focuses on the idea that opaque assets are related to stock price crash risk, which is the likelihood of extreme bad firm-specific returns. As outlined in previous studies (e.g., Jin and Myers, 2006), managers tend to withhold bad news for as long as possible, to safeguard their job and protect their compensation (Kothari et al., 2009). 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. 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). 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., 2018).

With reference to the banking literature, Cohen et al. (2014) provide evidence that earnings management and financial statements opacity increase crash risk in banks as in other industries. However, earnings management has a small predictive power for downside risk during normal times, which increases significantly during crisis periods. Dewally and Shao (2013) measure the opacity of banks' operations with the use of interest rate and foreign exchange financial derivatives, finding a positive relationship with crash risk. To the best of our knowledge, the only paper relating equity tail risk to securitization is Trapp and Weiß (2016). However, our paper is significantly different, for at least three reasons: first, they only consider the 2007-2009 period of the GFC, focusing on US banks, while we cover a much longer interval (2000-2017) considering European banks. Second, they use two indicators of tail risk - the Dynamic Marginal Expected Shortfall and the Conditional Value at Risk - that measure, respectively, the bank's tendency to register heavy losses when the market plummets or the individual bank's contribution to the whole system's tail risk. These measures, often used as indicators of systemic rather than crash risk, are strongly different from the ones adopted in this paper (described in next sections), which are based on extreme negative events observed in the far-left tail of the bank-specific return distribution. Consequently, the focus is on bank-specific features rather than on co-movement with the market. Finally, we use a different approach to deal with endogeneity, based on a dynamic panel model rather than to the use of lagged independent variables.

2.3 Theoretical background and research question

Overall, the relationship between securitization activity and crash risk remains an open question. There is also a dearth of papers focusing on tail risk measures (or crash risk and expected shortfall measures); none provide causal evidence that securitization either decreases or increases crash 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, despite the evidence on the direct link between opacity and crash risk. As outlined by Jones et al. (2013), opacity in the banking industry may arise from different sources, including incomplete disclosure and fundamental complexity of business that makes accurate valuation nearly impossible. In their empirical analysis, based on a sample of listed US banks and financial holding companies over a pre-crisis period (2000–2006), they identify main opaque assets with commercial loans, residential loans, and typical securitization products, such as asset and mortgage-based securities. Using a more recent sample (2005-2014), including banks based in Europe, Kosmidou et al. (2017) also find a relationship between crash risk and loan opacity. How does this apply to our case? On the one hand, there are reasons to expect that recourse to securitization is associated with higher crash risk. Securitization maybe a quite opaque process itself; originating banks may hold in their portfolio some asset and mortgage backed securities deriving from securitization, which are sometimes difficult to evaluate. And, most importantly, banks may use liquid funds obtained by securitization to lend more to risky borrowers and retain riskier loans. On the other hand, a competing hypothesis is that securitization is associated with lower crash risk. Following previous studies, the most opaque assets in the banking business are loans, especially those that are granted to counterparties without a rating and difficult to evaluate (e.g., commercial and residential loans). Using securitization banks are able to sell (risky) loans, obtain liquid funds, and then reduce the opaqueness of their balance sheet. Which effect is prevailing remains an empirical question and is the focus of this paper: Does securitization activity decrease the originators' crash risk?

We also test if the relationship between securitization and crash risk differs depending on the underlying assets of securitization deal. More specifically, we identify a subsample of less complex securitizations (i.e., loans with a high degree of standardization, collateralization and granularity) and more complex securitizations[6] (i.e., high number of complex loan arrangements, which are typically difficult to evaluate for potential investors and, hence, are perceived as

[6] Farruggio and Uhde (2015)

riskier by them). This leads to an additional test, where we examine whether the relationship between securitization and crash risk differs for more and less complex securitizations?

We define more complex securitizations as 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); less complex securitizations: transactions when the underlying asset type is not a CDO. This distinction is consistently with the additional complexity of CDOs (see also Anderson 2019).

3. Empirical Methodology

Our identification strategy addresses the issue of potential endogeneity in establishing a causal relationship between securitization and the downside 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 crash risk).

We follow some recent papers proposing a dynamic panel data approach to address the endogeneity issue (Gopalan, et al., 2016; Fiordelisi et al., 2019). The adopted approach is very similar to Fiordelisi et al. (2019), using a dynamic panel estimation to assess the impact of issuing contingent convertible bonds on several indicators of bank crash risk. 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[7]. Specifically, we run the following regression:

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

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 measures the effect of securitization on bank crash risk in the following year. 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 crash 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), both in lags (at the time t-1). At the country level, we consider the dynamic of prices (INFLATION) to control for both economic and financial conditions[8]. We also 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 a sample of European banks, we also consider the Eurozone sovereign debt crisis, which was in its most acute phase until 2013[9]. Finally, to alleviate a potential missing (or

[7] 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. Obviously, these leads and lags may also be equal to zero.

[8] We also tried to include other controls at the bank level, such as the GDP growth rate and the level of concentration in the banking industry measured by the HHI index, and results remains unaltered.

[9] We thank an anonymous referee for suggesting the inclusion of a crisis dummy in all our models.

omitted) variables problem, we also include in our model bank- and year-fixed effects (respectively A_i and B_t). We calculate robust standard errors clustered at the country level.

Following recent studies, we consider as dependent variables 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[10]). From this model, we obtain bank-specific returns as the residual from regression (2)[11].

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*).

It is very important to stress that crashes are not effective realizations, but represent bank-specific extreme price movements over and above those due to common risk factors. Hence, each crash is defined from an idiosyncratic perspective and identifies an extreme event

[10] The use of a general, rather than a banking industry market index, is consistent with past literature. For example, both Dewally and Shao (2013) and Callen and Fang (2015) use the CRSP value-weighted market index return.
[11] Following Hutton et al. (2009), we adopt a log transformation of residuals from equation (2) which are highly skewed. Specifically, we use bank-specific returns given by the log of one plus the residual.

with respect to the bank-specific distribution of returns, which are those not explained by general market movements.

Following Hutton et al. (2009) and Callen and Fang (2015), we also consider the negative conditional skewness (NCSKEW), which is calculated as:

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

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:

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

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. A higher value for DUVOL corresponds to a stock being more ''crash prone.''

As a second step, we run a model considering the potential impact of the global financial crisis. 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 crash 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[12]. 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 a homogenous sample, not biased by differences in accounting standards, loan portfolio management techniques and business policies. The sample is based on 11 European countries: Austria, Belgium, Denmark, Germany, France, Italy, Netherlands, Spain, Sweden, Switzerland, and United Kingdom[13].

Our sample covers the period from 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

[12]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.
[13] Although our sample is a quite small, it covers all countries (Austria, Belgium, Denmark, Germany, France, Italy, Netherlands, Spain, Sweden, Switzerland, and United Kingdom) represented by percentages spanning from 5.54% (i.e. Austria) to 12.93% (i.e. Sweden).

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 37 listed banks for a total number of 433 bank-year observations. All our sample securitizing banks are frequent issuers, with the exception of Nordea and Swed bank for which only one security transaction is recorded over the entire investigation period. If a bank securitizes several 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_MC and SEC_LC. The first one, SEC, is the ratio of a banks' cumulative securitization volume to total assets, while SEC_MC and SEC_LC refer to the complexity of the underlying assets. Specifically, following Anderson (2019), 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 less complex securitizations when the underlying asset type is not a CDO.

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

Table 1, Panel A 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) the average value 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. Panel B details the sample classified by country. The UK (16.4%), followed by Spain (13.16%) and Sweden (12.93%) account for the most securitizations.

[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). 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 less complex securitizations (SEC_LC). However, they all have a positive correlation with more complex securitizations (SEC_MC). Table 2 appears to provide some preliminary evidence related to our research questions. However, we consider this evidence preliminary 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 crash 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 always 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 12.8% and 12.7% (respectively in Models 1a and 1b); to a decrease of *NCSKEW* of about 9.56% and 9.69% (respectively in Models 2a and 2b), and to a decrease of *DUVOL* of about 5.54% and 5.71% (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 are consistent with those obtained from previous studies, finding a reduction in the crash risk of the banks in the year of the securitization (negative contemporaneous effect), but an increase in the crash 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 crash 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, 2006; 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 (Instefjord, 2005).

Second, we distinguish the underlying asset portfolio of securitization transactions, running model in equation (1), respectively, for more and less-complex securitizations. For more-complex 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_MC* is positive and statistically significant at the 5% confidence level for crashes minus jumps (*CRASH_JUMP*), providing some evidence that banks may securitize opaque assets in anticipation of an increase in crash risk. For all other risk measures, there are no significant results at the 10% confidence level or less.

[INSERT TABLE FOUR ABOUT HERE]

Finally, we run the model in equation (1) for less-complex securitizations and the results are shown in Table 5. Our findings are very similar to the general model in Table 3. More specifically, the less-complex subsample confirms the results of the overall sample: there is evidence of a contemporaneous risk-reduction effect of securitization and a post-event increase in crash risk. However, in the case of less-complex 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 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 crash risk reduction effect, followed by an increase in crash risk. Overall, this leads to a weak crash risk reduction effect, which is statistically significant at the 10% confidence level only for crashes minus jumps (*CRASH_JUMP*). During crisis periods, we must also consider 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 cannot reject the null hypothesis that the effect of securitization on crash risk was null during the crisis period. Overall, we do not find any evidence that securitization, during crisis periods, reduces crash risk.

[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 still consider the stock price dynamic of each originating bank but taking into account the most common indicators of tail risk i.e., Value at Risk (*VaR*) and Expected Shortfall (*ES*) rather than crash risk. For both indicators, we use a historical simulation approach, with a confidence level of 97.5% and a one-week holding period, using one year of stock weekly returns[14].

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 9.60‰ and 9.35‰ respectively in Models 1a and 1b, and to a decrease of the ES of about 9.70‰ and 9.45‰ 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]

[14] We do not use a 99% confidence interval because we have weekly returns over one year of data, and then about 50 observations a year. As a consequence, using a tail of 1% would lead to cut observations in a way that we obtain the same value for VAR and ES.

Finally, as a further robustness check, we adopt a GMM framework, in which lagged differences of the dependent variables and our main macroeconomic indicator are used to generate the instruments. Results are shown in Table 10 for our basic specification, using the total volume of securitization. When statistically significant at the 10% confidence level or less, results confirm our main finding of a negative relationship between the use of securitization and the level of risk perceived by investors[15].

[INSERT TABLE TEN ABOUT HERE]

7. Conclusions

Our paper examines whether securitizing banks tend to be more prone to crash risk. By analyzing a sample drawn on European commercial listed banks included in the Euro Stoxx 600 index and covering all securitization activity during the period 2000-2017, we provide novel evidence that there is a reduction in bank crash risk during the year a bank securitizes (a negative contemporaneous effect), and an increase in risk after the securitization issuance (positive post-securitization effect). We also find that, in more complex securitizations, banks may securitize opaque assets in anticipation of an increase in crash risk, pointing to a reverse causality problem. In less-complex securitizations, we show a contemporaneous risk-reduction effect of securitization and a post-event increasing crash risk. Finally, we also find 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. First, we show that securitization enable banks to immediately reduce crash risk and, thus, a more efficient securitization market is beneficial for bank stability.

[15] Distinguishing between high and low risk securitization, results show that the negative relationship between securitization and risk is weaker for the former.

Second, the negative effect found in the year after the securitization show that it is important to assess how banks employ financial resources made available by securitization. Finally, our results support that disclosure requirements should be enhanced to let investors to capture whether banks securitize opaque assets in anticipation of an increase in crash risk.

Table 1 – Descriptive Statistics

In Panel A we report the mean, standard deviation, minimum and maximum of the variables used in our empirical analysis. In Panel B, we categorize the observations according to country. In the sample, Austria (AT), Belgium (BE), Switzerland (CH), Germany (DE), Denmark (DK), Spain (ES), France (FR), UK (GB), Italy (IT), Netherlands (NL), and Sweden (SE) are represented.

Panel A – Descriptive statistics

Variables	Obs	Mean	Std	Min	Max
SEC	433	0.01395	0.02843	0.00000	0.24499
SEC_MC	433	0.00156	0.00463	0.00000	0.04610
SEC_LC	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

Panel B – Observations by country

Country	*Freq.*	*Percent*	*Cum.*
AT	24	5.54	5.54
BE	15	3.46	9.01
CH	35	8.08	17.09
DE	25	5.77	22.86
DK	45	10.39	33.26
ES	57	13.16	46.42
FR	48	11.09	57.51
GB	71	16.4	73.9
IT	45	10.39	84.3
NL	12	2.77	87.07
SE	56	12.93	100
Total	433	100	

Table 2 – Correlation matrix

	Sec	Sec_mc	Sec_lc	Crash_jump	Ncskew	Duvol	Var_0975	Es_0975	Size	Tier1_	Inf
SEC	1.0000										
SEC_MC	0.7826	1.0000									
SEC_LC	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), inflation and crisis. 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	0.0598	0.0709	0.0200	0.0258	0.00449	0.00967
	(0.0405)	(0.0426)	(0.0328)	(0.0329)	(0.0341)	(0.0340)
SEC	-0.128**	-0.127**	-0.0956**	-0.0969**	-0.0554	-0.0571*
	(0.0432)	(0.0425)	(0.0403)	(0.0385)	(0.0310)	(0.0294)
POST_SEC	0.0425	0.0433	0.0444	0.0463	0.0197	0.0220
	(0.0594)	(0.0619)	(0.0490)	(0.0489)	(0.0300)	(0.0284)
$SIZE_{t-1}$		0.281*		0.108		0.0826
		(0.144)		(0.139)		(0.0975)
$TIER\ 1_{t-1}$		-0.0784**		-0.0483		-0.0507
		(0.0335)		(0.0747)		(0.0396)
INF_t		0.0408		0.0395		0.0437
		(0.0336)		(0.0407)		(0.0347)
CRISIS		-0.0497		-0.0685		0.0208
		(0.283)		(0.316)		(0.190)
Constant	-0.186	-0.0240	-0.0999	0.0339	-0.0346	-0.00858
	(0.106)	(0.223)	(0.159)	(0.286)	(0.101)	(0.194)
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		-0.084*		-0.0506		-0.0351

Table 4 – More complex 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 more-complex 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), inflation and crisis. 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_MC	0.0535**	0.0573**	0.0106	0.0124	0.00601	0.00748
	(0.0236)	(0.0235)	(0.0192)	(0.0187)	(0.0216)	(0.0235)
SEC_MC	-0.0503	-0.0454	-0.0163	-0.0140	-0.0150	-0.0132
	(0.0405)	(0.0393)	(0.0358)	(0.0353)	(0.0235)	(0.0236)
POST_SEC_MC	0.00241	0.000483	0.0112	0.0104	0.0240	0.0235
	(0.0312)	(0.0324)	(0.0350)	(0.0362)	(0.0200)	(0.0208)
$SIZE_{t-1}$		0.298**		0.132		0.101
		(0.123)		(0.139)		(0.0931)
$TIER\ 1_{t-1}$		-0.0749*		-0.0470		-0.0486
		(0.0346)		(0.0724)		(0.0389)
INF_t		0.0386		0.0384		0.0439
		(0.0392)		(0.0432)		(0.0382)
CRISIS		-0.0584		-0.0714		0.0220
		(0.282)		(0.313)		(0.187)
Constant	-0.182	-0.0272	-0.0929	0.0298	-0.0237	-0.0113
	(0.102)	(0.223)	(0.156)	(0.287)	(0.102)	(0.193)
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_MC + POST_SEC_MC		-0.0450		-0.0036		0.0103

Table 5 – Less Complex 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 less-complex 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), inflation and crisis. 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_LC	0.0448	0.0566	0.0155	0.0216	0.00131	0.00678
	(0.0443)	(0.0475)	(0.0347)	(0.0355)	(0.0348)	(0.0345)
SEC_LC	-0.122**	-0.123**	-0.101**	-0.102**	-0.0558*	-0.0580*
	(0.0422)	(0.0418)	(0.0398)	(0.0388)	(0.0307)	(0.0298)
POST_SEC_LC	0.0424	0.0440	0.0442	0.0466	0.0120	0.0147
	(0.0592)	(0.0617)	(0.0467)	(0.0460)	(0.0296)	(0.0273)
$SIZE_{t-1}$		0.276*		0.105		0.0802
		(0.145)		(0.139)		(0.0980)
$TIER\ 1_{t-1}$		-0.0794**		-0.0490		-0.0514
		(0.0336)		(0.0755)		(0.0397)
INF_t		0.0404		0.0394		0.0433
		(0.0323)		(0.0400)		(0.0341)
CRISIS		-0.0500		-0.0690		0.0201
		(0.283)		(0.316)		(0.190)
Constant	-0.185	-0.0227	-0.102	0.0343	-0.0377	-0.00890
	(0.107)	(0.222)	(0.158)	(0.286)	(0.101)	(0.194)
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_LC + POST_SEC_LC		-0.0786*		-0.0556		-0.0433*

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), inflation and crisis. 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	0.0827	0.0932	0.0457	0.0509	0.00986	0.0152
	(0.0649)	(0.0663)	(0.0497)	(0.0494)	(0.0432)	(0.0429)
SEC	-0.232**	-0.234**	-0.227**	-0.230**	-0.133*	-0.136*
	(0.0895)	(0.0915)	(0.0766)	(0.0774)	(0.0621)	(0.0624)
POST_SEC	0.138*	0.143**	0.169**	0.173***	0.102*	0.106**
	(0.0654)	(0.0641)	(0.0548)	(0.0525)	(0.0473)	(0.0438)
$SIZE_{t-1}$		0.289*		0.105		0.106
		(0.136)		(0.130)		(0.0962)
$TIER\ 1_{t-1}$		-0.0771*		-0.0492		-0.0483
		(0.0347)		(0.0756)		(0.0410)
INF_t		0.0422		0.0429		0.0448
		(0.0315)		(0.0395)		(0.0331)
CRISIS		-0.0571		-0.0713		0.0113
		(0.283)		(0.310)		(0.191)
*PRE_SEC*CRISIS*	-0.118	-0.112	-0.114	-0.106	0.00409	0.0122
	(0.177)	(0.187)	(0.136)	(0.145)	(0.0496)	(0.0520)
*SEC*CRISIS*	0.298	0.282	0.363	0.361	0.106	0.104
	(0.394)	(0.378)	(0.290)	(0.284)	(0.145)	(0.139)
*POST_SEC*CRISIS*	-0.170	-0.181	-0.222**	-0.226**	-0.163**	-0.167**
	(0.103)	(0.109)	(0.0933)	(0.0972)	(0.0655)	(0.0669)
Constant	-0.179	-0.0245	-0.0900	0.0396	-0.0272	-0.0150
	(0.107)	(0.218)	(0.158)	(0.282)	(0.101)	(0.196)
Observations	433	433	433	433	433	433
Bank fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
LINEAR COMBINATION						
a) SEC+POST_SEC		-0.0912*		- 0.0566		-0.0294
*b) SEC*CRISIS+POST_SEC*CRISIS*		0.1005		0.1350		-0.0630
c) A+B		0.0093		0.0784		-0.0925

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-week, 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), inflation and crisis. 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	0.00134	0.00221	0.00143	0.00230
	(0.00262)	(0.00295)	(0.00268)	(0.00302)
SEC	-0.00960**	-0.00935**	-0.00970**	-0.00945**
	(0.00313)	(0.00300)	(0.00316)	(0.00303)
POST_SEC	0.00272	0.00259	0.00266	
	(0.00274)	(0.00267)	(0.00279)	
$SIZE_{t-1}$		0.0265*		0.0263
		(0.0145)		(0.0149)
$TIER\ 1_{t-1}$		-0.00718		-0.00736
		(0.00615)		(0.00623)
INF_t		0.00144		0.00146
		(0.00279)		(0.00284)
CRISIS		-0.0214**		-0.0223**
		(0.00693)		(0.00707)
Constant	0.127***	0.106***	0.131***	0.108***
	(0.0106)	(0.00665)	(0.0115)	(0.00673)
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		-0.0068**		- 0.0069**

Table 8 – Robustness check: More-complex 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-week, 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 more-complex 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), inflation and crisis. 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_MC	-0.00187*	-0.00159	-0.00188*	-0.00161
	(0.000949)	(0.00110)	(0.000964)	(0.00112)
SEC_MC	-0.00369*	-0.00323*	-0.00368*	-0.00322*
	(0.00172)	(0.00159)	(0.00173)	(0.00160)
POST_SEC_MC	0.00322	0.00300	0.00309	0.00288
	(0.00194)	(0.00194)	(0.00194)	(0.00193)
$SIZE_{t-1}$		0.0267*		0.0265*
		(0.0138)		(0.0142)
$TIER\ 1_{t-1}$		-0.00712		-0.00730
		(0.00615)		(0.00624)
INF_t		0.00135		0.00137
		(0.00289)		(0.00293)
CRISIS		-0.0212**		-0.0221***
		(0.00680)		(0.00696)
Constant	0.129***	0.106***	0.133***	0.108***
	(0.0107)	(0.00650)	(0.0115)	(0.00659)
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_MC + POST_SEC_MC		-0.0002		-0.0003

Table 9 – Robustness check: Less-complex 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-week, 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 less-complex 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), inflation and crisis. 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_LC	0.00160	0.00256	0.00170	0.00266
	(0.00269)	(0.00300)	(0.00275)	(0.00307)
SEC_LC	-0.00939***	-0.00922***	-0.00951***	-0.00934***
	(0.00246)	(0.00232)	(0.00248)	(0.00235)
POST_SEC_LC	0.00135	0.00129	0.00132	0.00126
	(0.00252)	(0.00237)	(0.00258)	(0.00243)
$SIZE_{t-1}$		0.0268*		0.0266
		(0.0146)		(0.0150)
$TIER\ 1_{t-1}$		-0.00726		-0.00744
		(0.00618)		(0.00626)
INF_t		0.00142		0.00144
		(0.00277)		(0.00281)
CRISIS		-0.0214**		-0.0223***
		(0.00688)		(0.00702)
Constant	0.127***	0.106***	0.130***	0.108***
	(0.0106)	(0.00661)	(0.0114)	(0.00669)
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_LC + POST_SEC_LC		-0.0079***		- 0.0081***

Table 10 – Robustness check: GMM estimation

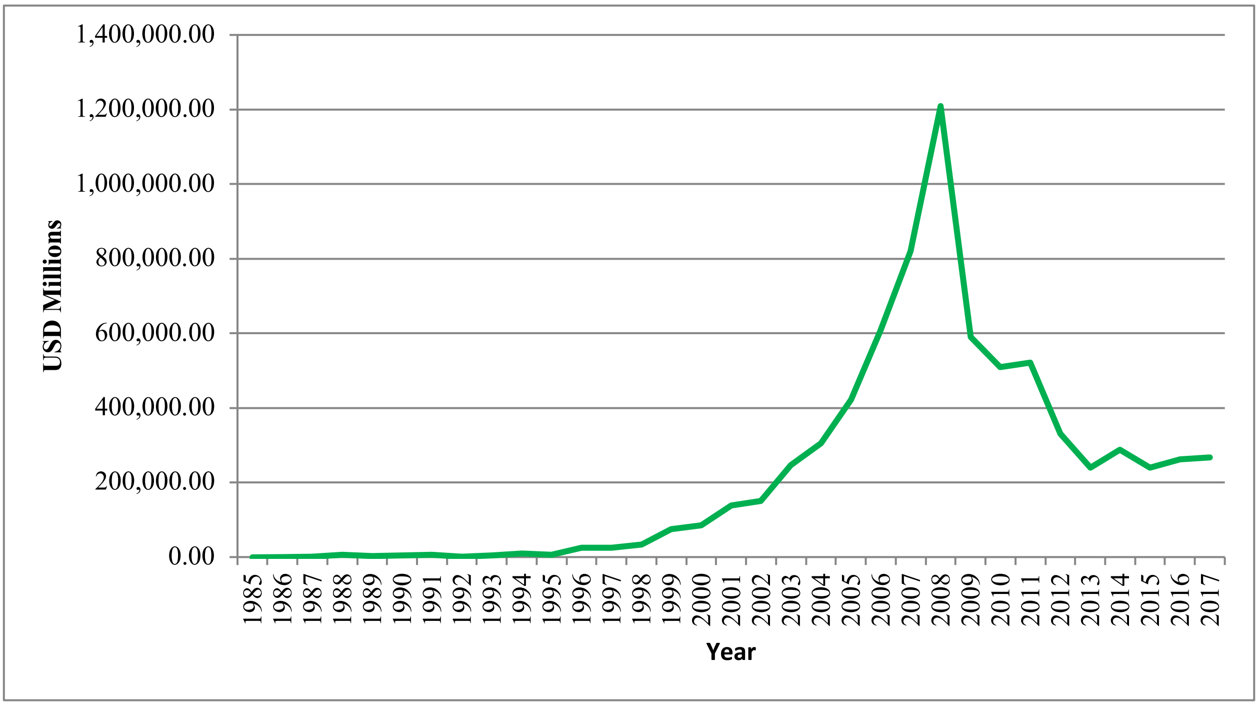
This table reports results from a GMM estimation including the first lag of each dependent variable (a measure of stock price tail risk). The main variables of interest are the indicator variables identifying the use of securitization as defined in Table 1. All continuous variables are standardized and winsorized at the 1 and 99 percentiles. Control variables are Size, Tier 1 ratio (which are lagged one year), inflation and crisis. Robust standard errors are reported in parentheses. ***, **, * denotes that estimates are statistically significant at the 1, 5 and 10% levels.

VARIABLES	(1) crash_jump	(2) ncskew	(3) duvol	(4) var_0975	(5) es_0975
SEC	0.0352	-0.2067	-0.2166	-0.0973***	-0.0970***
	(0.1468)	(0.1682)	(0.2301)	(0.0355)	(0.0361)
$SIZE_{t-1}$	0.4636***	0.4418***	0.2605***	0.0016	0.0007
	(0.0979)	(0.1212)	(0.0642)	(0.0116)	(0.0121)
$TIER\ 1_{t-1}$	0.1770	-0.0616	-0.1533	0.0024	0.0025
	(0.1971)	(0.2093)	(0.1893)	(0.0156)	(0.0157)
INF_t	1.1275	1.1482*	0.7985	0.2028***	0.2053***
	(0.8643)	(0.6471)	(0.5603)	(0.0498)	(0.0513)
CRISIS	0.1323	0.1014	-0.0102	-0.0813***	-0.0824***
	(0.2097)	(0.2015)	(0.1511)	(0.0220)	(0.0226)
$CRASH\_JUMP_{t-1}$	-0.4597**				
	(0.2049)				
$NCSKEW_{t-1}$		-0.3178**			
		(0.1447)			
$DUVOL_{t-1}$			-0.3627		
			(0.2279)		
VAR_0975_{t-1}				-0.2835**	
				(0.1203)	
ES_0975_{t-1}					-0.2866**
					(0.1213)
Observations	378	378	378	378	378
Number of id	34	34	34	34	34
Sargan Hansen test	23.10	25.63	23.00	28.01	28.03
p-value	0.339	0.221	0.344	0.140	0.139

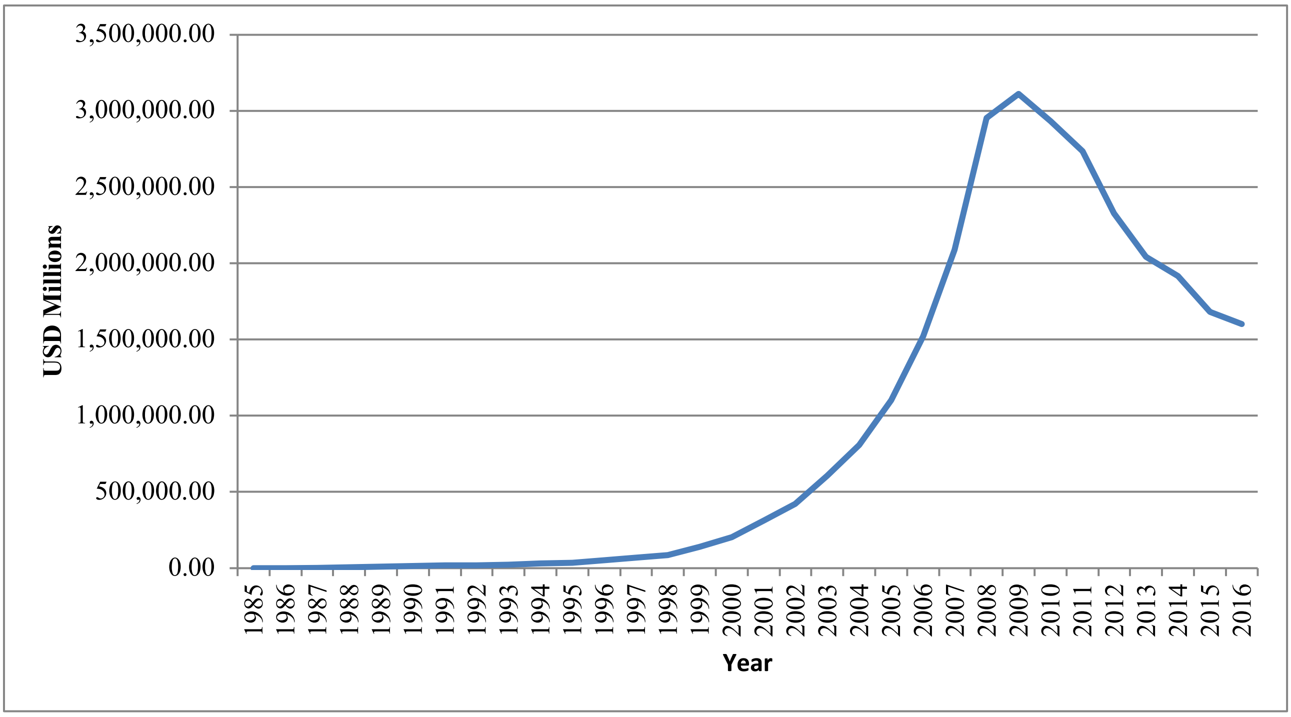
Figure 1 – European Securitization - Issuance

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). Both charts cover major regulatory interventions such as Basel III (2009), Capital Requirements Directives (CRD) II (2011), CRD III (2010), CRD IV (2013) and Simple, Transparent and Standardized (STS) securitizations (set out in 2017, but still in progress). 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_MC#	Ratio of a banks' cumulative more-complex 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_MC#	Ratio of a banks' cumulative more-complex 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_MC#	Ratio of cumulative more-complex 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_LC#	Ratio of a banks' cumulative less-complex securitization volume in the current year *t* to total assets, when the underlying asset type is not a collateralized debt obligation – CDO
POST_SEC_LC#	Ratio of a banks' cumulative less-complex securitization volume done in the previous year to total assets, when the underlying asset type is not a collateralized debt obligation – CDO
PRE_SEC_LC#	Ratio of cumulative less-complex 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§	Inflation per year

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-week, 97.5%
ES_0975+	Expected shortfall, one-week, 97.5%

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