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Determinants of loan securitization in European banking

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Abstract: Analyzing 75 securitizing and non-securitizing stock-listed banks in the EU-13 plus Switzerland over the period from 1997 to 2010, this paper provides empirical evidence that loan securitization in Europe is a composite decision based on bank-specific as well as market- and country-specific determinants. In addition, we find that these determinants remarkably change when separately investigating securitization transactions during the pre-crisis and crisis period. Moreover, results from several subsample regressions reveal that determinants of loan securitizations in Europe depend on the transaction type, the underlying asset portfolio and the regulatory and institutional environment under which banks operate.

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1. Introduction

During the years before the global financial crisis from mid-2007, loan securitization by European banks has experienced a tremendous growth with regard to both numbers and volumes of securitization transactions (ECB, 2011; AFME, 2012). Most commonly accepted incentives for European banks to engage in the securitization business include (i) the reduction of the bank's overall credit risk exposure through portfolio diversification and specification, (ii) the use of securitization as an alternative funding tool and (iii) the reduction of economic and regulatory capital requirements (e.g., Michalak and Uhde, 2011).

However, taking into account the disastrous consequences of the financial crisis, policy makers, regulators and academics have emphasized several misalignments in the securitization market. In this context, it is commonly suggested that in particular structured finance products like securitizations may have fostered the subprime mortgage crisis (ECB, 2008). As a consequence, regulators have responded with extensive regulatory reforms including new risk retention rules as well as stricter liquidity, capital and transparency requirements as regards future securitization transactions by banks (BCBS, 2011 and 2012).

Against this background, the paper at hand analyses determinants of loan securitizations by European banks with a special emphasis on the pre-crisis and crisis period. While most of earlier empirical studies for Europe primarily focus on the impact of securitization on bank risk and wealth effects in an ex post scenario (e.g., Michalak and Uhde, 2011; Uhde et al., 2012), to date only a few (empirical) studies address the question on a bank's motivation to securitize in an ex ante scenario (e. g., Bannier and Hänsel, 2008; Affinito and Tagliaferri, 2010). Moreover, an identification of the main drivers of securitization before and during the global financial crisis is of great interest, in particular for regulators who aim at restoring confidence in the securitization market and assessing the relevance of the recent initiatives to revitalize the market for structured finance products.

Our study complements and extends previous empirical work along several dimensions. *First*, to the best of our knowledge this is the first comprehensive study that empirically investigates the determinants of a bank's decision to engage in the securitization business while considering the years of the securitization boom in Europe on the one hand and the financial crisis period on the other hand. In this context the panel approach employed allows controlling for changes in the securitization business over time. *Second*, while existing studies primarily analyze bank-specific determinants for single countries, we perform a comprehensive cross-country analysis and investigate bank-, market- and country-specific as well as institutional factors that may influence a bank's decision to securitize loans. *And third*, the paper at hand extends the existing literature as we analyze the determinants of different securitization transaction by differentiating between the transaction type and the respective underlying asset portfolio.

The remainder of the paper is organized as follows. Section 2 provides the theoretical background and summarizes earlier empirical evidence on securitization determinants. Subsequently, Section 3 presents the empirical methodology. While our data and sources are described in Section 3.1, the empirical model is presented in Section 3.2. Section 4 discusses empirical results and finally, Section 5 concludes.

2. Theoretical background and prior empirical evidence on securitization determinants

2.1 Main characteristics of a securitization transaction

Generally, a securitization transaction can be defined as the transformation of illiquid assets (e.g., loans) into tradable securities. In a traditional securitization transaction the originator (typically a bank) transfers a pool of loans to a special purpose vehicle (SPV) which in turn refinances the purchase of these loans by the issuance of asset-backed securities. Acting between potential external investors and the originator, the SPV passes funding from selling these securities to the originator and transfers interest and principal payments from underlying loan agreements to investors (Jiangli et al., 2007, BCBS, 2011).

In case of a traditional *true sale* (cash) securitization transaction, the underlying pool of loans is completely transferred out of the bank's balance sheet and sold to the SPV. In contrast, by means of a *synthetic* securitization transaction, credit risk from underlying loans is transferred entirely or partly through funded (e.g., credit-linked notes, CLN) or unfunded (e.g., credit default swaps, CDS) credit derivatives while the loans remain on the bank's balance sheet.

Independent of the type of transaction, a typical securitization transaction is structured into different tranches with individual risk-return characteristics and strict subordination. Usually, less risky mezzanine and the least subordinated senior tranches are transferred out of the bank's balance sheet. In contrast, the more risky equity tranche ("first-loss piece") is retained by the bank and acts as a quality signal towards (less informed) investors since potential credit losses are at first absorbed by the holder of the first-loss piece (ECB, 2008). Moreover, next to this explicit arrangement, the originating bank may provide further credit support beyond its contractual obligations which is referred to as "implicit recourse" (Jiangli and Pritsker, 2008).

2.2. Determinant of loan securitizations

Theoretical models and empirical evidence suggest different motives for banks to engage in the securitization business. These motives can generally be differentiated in bank-specific and market- and country-specific determinants.

Bank-specific determinants

To begin with, banks have an incentive to use securitization as an alternative funding source by transforming loans into cash (Kothari, 2002). The *liquidity effect* is typically related to true sale transactions when a bank transfers parts of their loan portfolio to the SPV and in turn, receives liquidity from the issuance of loan backed securities by the vehicle. Thus, dependent on a bank's actual need for liquidity and the costs from holding traditional retail deposits (costs through deposit insurance and reserve requirements), securitization is an instrument to obtain an alternative funding source beyond traditional equity- and debt-financing.

Prior empirical studies provide clear evidence that the originating bank's liquidity position determines the decision to enter the securitization market. Analyzing securitization transactions issued by Spanish banks over the period from 1999 to 2006 and from 2000 to 2007 respectively, Martìn-Oliver and Saurina (2007) as well as Cardone-Riportella et al. (2010) find that securitization is predominantly driven by the banks' liquidity needs and search for alternative funding sources. Affinito and Tagliaferri (2010) confirm this finding for securitization transactions from Italian banks between 2000 and 2006. Similarly, Bannier and Hänsel (2008) analyze issuing banks from 17 European countries between 1997 and 2004 and provide evidence that a weak liquidity position triggers securitization.

The originating bank's *risk exposure* is described as a further determinant of loan securitization. In contrast to the traditional banking approach, which suggests that a bank originates loans and holds them in its banking book until maturity ("originate-to-hold" model), loan securitization refers to the "originate-to-distribute" model (Gorton and Pennacchi, 1995; Duffie, 2008; Purnanandam, 2011). Hence, following the "efficient contracting hypothesis" in this context (Minton et al., 2004), securitization is mainly employed in order to reduce a bank's exposure to credit risk by increasing the loan portfolio quality.

However, the effect of securitization on a bank's overall risk exposure is ambiguous (DeMarzo, 2005; Hänsel and Krahnen, 2007; Michalak and Uhde, 2011). *First*, the originating bank has no incentive to continue an extensive monitoring of borrowers once the credit risk has been transferred out of the bank's balance sheet (Pennacchi, 1988; Ambrose et al., 2005; Duffie, 2008). *Second*, due to information asymmetries between the issuing bank and external investors, the bank will typically retain the most risky tranche (first-loss piece) in its balance sheet and may additionally provide implicit recourse to the underlying loan portfolio in case of loan defaults (Dahiya et al., 2003; DeMarzo, 2005; Marsh, 2006; Duffie, 2008). *And third*, only those banks that exhibit a high loan portfolio quality and hence, a low exposure to credit risk, may profit from reputational advantages when they repeatedly enter the securitization market and place multiple transactions (Ambrose et al., 2005).

Against this background, credit risk transfer through securitization is limited and strongly depends on the relation between the transferred tail risk of senior (mezzanine) tranches and the amount of the retained default risks (Jiangli et al., 2007). While banks with a relatively high portion of risky assets in their balance sheets should be more prone to securitize in order to decrease their risk exposure, originators with higher portfolio quality are expected to realize a higher credit risk transfer at full compensation as the retention of risks is comparatively low (Calomiris and mason, 2004; Gorton and Souleles, 2006).

Corresponding to theoretical predictions, empirical evidence on the relationship between securitization and bank risk is also ambiguous. Affinito and Tagliaferri (2010) find that Italian banks suffering from higher loan portfolio risks tend to stronger engage in the securitization business. Similarly, empirical evidence provided by Bannier and Hänsel (2008) suggests that securitization is more likely for European banks which exhibit more risky loan portfolios. In contrast, Martìn-Oliver and Saurina (2007) do not find that a larger credit risk exposure spurs securitization transactions in the Spanish banking sector.

Turning to the banking regulation perspective, realizing *regulatory capital arbitrage* is described as a further determinant of loan securitization. The First Basel Capital Accord (Basel I) provided an opportunity for banks to reduce regulatory equity capital through securitization (Jones, 2000). The reason is that Basel I regulations encouraged banks to keep the major part of default risks within their balance sheets. Thus, as corporate and retail loans were not risk-adjusted but globally backed up with equity capital under Basel I, keeping the largest part of default risks within the first-loss piece provoked arbitrage profits if the amount of required regulatory equity capital was comparably lower when securitizing these assets (Ambrose et al., 2005; Bannier and Hänsel, 2008). Trying to mitigate this negative external effect, Basel II now follows a "substance over form principle" which more precisely determines the required regulatory capital for all retained tranches of a securitization (Blum, 2008; Johnston, 2009).[1] As a consequence, Basel II strongly stimulates incentives to transfer subordinated tranches and in particular, the first-loss piece, to external investors.

Empirical evidence on the regulatory capital arbitrage effect is ambiguous. Minton et al. (2004) analyze securitization transactions issued by regulated and unregulated U.S. banks between 1993 and 2002. They do not provide any empirical evidence that the opportunity to realize regulatory capital arbitrage spurs securitization activities. Martìn-Oliver and Saurina (2007) confirm these findings for Spanish banks. In contrast, Uzun and Webb (2007) employ securitization data from a sample of 112 financial institutions in the U.S. for the period from 2001 to 2005. They find that realizing regulatory capital arbitrage may be an incentive to securitize, however, evidence is based on the securitization of credit card receivables only.

[1] Nevertheless, opportunities to realize regulatory capital arbitrage even remain under Basel II regulations depending on the respective risk management approach and the relevant asset classes (e.g., Calem and LaCour-Little, 2004).

Finally, the *originator's performance* is considered as a determinant of securitization. The term "performance" is suggestive. On the one hand, it is argued that larger banks exhibiting a higher degree of risk management expertise and more efficient risk management systems perform better and securitize to a greater extent (Hänsel and Krahnen, 2007). On the other hand, it is suggested that securitization increases bank performance, i.e. securitization of credit risk enables banks to optimize loan portfolio returns through specialization, explore more profitable business opportunities and concentrate on core competences (Bartov, 1993; Beatty et al., 1995; Karaoglu, 2005).

Empirical evidence provided by Cardone-Riportella et al. (2010) generally supports theoretical arguments indicating that more efficient and larger banks securitize more frequently and may issue higher transaction volumes. In contrast, Bannier and Hänsel (2008) find that bank efficiency and size may be determinants of securitization as well, but their results also indicate that in particular less profitable banks more strongly engage in the securitization business.

Market- and country-specific determinants

An increasing strand of theoretical literature investigates the impact of banking market structures on securitization activities (e.g., Frankel and Yin, 2011; Hakenes and Schnabel, 2010). In particular, the majority of studies concentrate on the relationship between *market competition* and loan securitization. In this context, it is commonly argued that banks operating in more competitive markets are less profitable, have lower capital buffers and hence, suffer from decreasing risk bearing capacities. As a consequence, banks are forced to securitize even (highly) profitable but risky loans resulting in an increase in the quality of the underlying loan pools. Accordingly, an increase in the supply of high-quality securitization transactions will spur the demand for these financial products, which will finally induce an overall increase in securitization activities (Hakenes and Schnabel, 2010).

Turning to country-specific determinants, securitization activities may also be driven by the macroeconomic environment. While the state of the economy accounts for possible country-specific differences due to the size of the real economy and the effect on securitization, the impact of economic growth on loan securitization is more distinct. As economic growth is typically related to an increase in investment opportunities, securitization enables banks to create necessary liquidity to serve the higher demand for loans during economic boom phases (Adrian et al., 2010). Moreover, several studies stress the negative impact of economic growth on lending standards (Maddaloni and Peydró, 2011; Dell'Ariccia et al., 2012). Taking this into account, it is suggested that banks will increase lending towards riskier borrowers and, thus, will have a stronger incentive to restructure their asset portfolios by means of securitization (Bannier and Hänsel, 2008; Michalak and Uhde, 2011).

3. Empirical methodology

3.1. Data and sources

Notes on variables and data sources are presented in Table 1 in Appendix A. While Table 2a and 2b illustrate descriptive statistics, Figures 1 and 2 show the distribution of securitization transactions over the entire sample period. Figure 3 presents frequent securitizers by the number and volume of securitization transactions whereas Figure 4 displays the percentage of sample banks that engage in the securitization business per year.

3.1.1. Dependent variable

Our sample includes securitizing and non-securitizing banks across the EU-13 and Switzerland.[2] Following related studies (see Minton et al. 2004; Michalak and Uhde, 2011) the analysis focuses on stock-listed banks only in order to obtain a homogenous sample that is not „biased" by differences in accounting standards, loan portfolio management techniques and business policies.[3] Corresponding to the start of securitization activities in the European banking sector at the end of the 1990s (ECB, 2007) the sample covers the period from 1997 to 2010.[4] We start with an initial sample of 103 stock-listed banks but are forced to exclude banks due to data availability reasons and in order to address a potential survivorship bias.[5] These adjustments finally reduce our sample to 75 stock-listed banks of which 60 have issued

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[2] The EU-13 comprises Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden and the United Kingdom. We omit securitization transactions from banks located in Finland and Luxembourg since we are not able to clearly assign securitization transactions to respective originating banks in these countries. We additionally include Switzerland for two reasons. First, even though Switzerland is not part of the EU / EMU the Swiss banking sector is strongly entangled with the European banking market. Second, several large securitization transactions are observed especially at UBS and Credit Suisse. We exclude Switzerland from our baseline regressions as a robustness check. However, as we do not obtain remarkably different results, we do not present them in this paper but provide them on request.

[3] For example, several non-stock-listed savings banks in Europe have own internal credit pools on a group-level to manage their loan portfolios. Thus, instead of selling securitized loans to capital market investors these banks rather use the internal credit pool to diversify loan portfolio risk. Furthermore, several credit cooperatives, which primarily act on behalf of their customers as members of the bank, are not allowed to sell loans to external investors at all.

[4] Due to policy responses in the context of the financial crisis and related changes within the regulatory framework we avoid possible biases in our estimation results by restricting the sample period to the year 2010.

[5] A survivorship bias is likely to occur due to mergers and acquisitions within the European banking industry over the sample period from 1997 to 2010. Some banks in our sample (1997-2010) no longer existed when data was collected in January 2008 and March 2010. We address this issue by omitting those banks that were involved in a merger or were acquired by another bank and keep the new combined company or the acquirer or in our sample.

at least one securitization transaction and 15 have never securitized during the entire sample period.

Among the 60 securitizing banks, some institutions issued more than one securitization transaction (frequent issuers) which leads to a total of 950 securitization transactions over the entire sample period of 14 years. Volumes of multiple transactions by one respective bank in one respective year were cumulated and subsequently included in the Tobit regression model (Section 3.2) resulting in 840 observations (60 banks over 14 years). Banks that have never securitized during the entire sample period were included with a transaction volume of zero resulting in additional 210 observations (15 banks over 14 years). Figure 3 shows frequent securitizers by the number and volume of securitization transactions and Figure 4 displays the percentage of sample banks that engaged in the securitization business per year.

The unique sample of 950 securitization transactions issued by the 60 stock-listed bank holdings is obtained from offering circulars and presale reports provided by Moody's, Standard & Poor's and FitchRatings. These reports provide detailed information on securitization issue dates, types and structures of the transactions as well as the underlying reference portfolio. Figures 1 and 2 illustrate the growing importance of securitization for our sample banks over the first decade with numbers and transaction volumes of securitization reaching a peak in 2007, followed by a decline as a consequence of the financial crisis starting in mid-2007. The descriptive statistics of transaction types and the underlying asset portfolios is given in Table 2a. As shown, the cumulated volume of all securitization transactions amounts to € 2,099.4 billion.[6] As further indicated, true sale transactions account

[6] As reported by the Association for Financial Markets in Europe (AFME) the cumulated volume of securitization transactions between 1997 and 2010 amounts to € 3,778.7 billion for the EU-15. Accordingly, our sample of 60 stock-listed banks covers nearly 56 percent of the entire cumulated volume. Note however, that the entire cumulated volume for the EU-15 includes securitization transactions by listed and non-listed banks, other financial intermediaries, industrial companies as well as governmental agencies. Unfortunately,

for approximately two thirds and synthetic transactions for one third of our transactions. Furthermore, our sample of securitizations is mainly represented by *Residential Mortgage Backed Securities* (RMBS; € 1,209.9 billion) and *Collateralized Debt Obligations* (CDOs; € 0,653.4 billion). The distribution of these different securitization transaction types over time is also displayed in Figures 1 and 2.

3.1.2. Explanatory variables

We retrieve bank balance sheet data from the BankScope database compiled by FitchRatings and provided by Bureau van Dijk. The history of banks' stock prices originates from the Datastream Database provided by Thomson Financial Services. Macroeconomic data is retrieved from the World Development Indicator (WDI) database provided by the World Bank.

All explanatory variables are included in the regression model on an annual basis. In the following, we present variables that are included in our baseline regressions. We substitute some of these variables by alternative measures during robustness checks in Section 4.2.

Bank-specific determinants

To begin with, we proxy a bank's liquidity position and funding needs by the ratio of liquid assets to deposits and short-term funding (*Liquidity*). Referring to theoretical arguments and results from prior empirical studies as discussed in Section 2.2., the incentive to securitize should be higher for banks with lower liquidity ratios and hence, a more pronounced lack of liquidity. We therefore expect a negative sign of the liquidity measure.

We further include the ratio of a bank's loan loss reserves to gross loans (*LL Reserves*) to proxy a bank's exposure to credit risk. Larger loan loss reserves suggest a decrease in a

the amount of the cumulated volume for the relevant sample period by EU-15 banking institutions is not separately available.

bank's loan portfolio quality and an increase in a bank's exposure to credit risk. Taking into account that theoretical predictions and empirical evidence suggest both, a positive and negative impact of a bank's credit risk exposure on the decision to securitize loans, the statistical effect of our control variable is ambiguous.

Turning to the regulatory capital arbitrage hypothesis, we include the ratio of the bank's Tier1 capital to risk weighted assets (*Tier1*). In line with theoretical arguments, we generally expect that banks with lower capital ratios more strongly engage in the securitization business in the earlier years under Basel I regulations. However, as the introduction of the revised Basel framework (Basel II) in 2006 has reduced the banks' opportunities to realize regulatory capital arbitrage through securitization, this effect may have been diminished.[7] Moreover, better capitalized banks may be generally less prone to realize regulatory capital arbitrage through securitization. Taking this into account, the statistical impact of the Tier1 measure is ambiguous.

As regards the originating bank's performance, we employ the cost-to-income ratio (*CIR*) as a commonly accepted proxy that measures the efficiency of a bank's risk management process and system. Referring to theoretical arguments and prior empirical evidence suggesting that banks with more efficient risk management systems generally perform better and stronger engage in securitization activities, we expect a negative sign of the cost-to-income ratio.[8]

Finally, following related empirical studies, we include the log of a bank's total assets (*Size*) to account for the impact of a bank's size on its securitization activities. The effect of bank size on securitization is ambiguous. If bank size is a proxy for efficiency, we should

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7 Analyzing different subsamples over time in Section 4.1 (pre-crisis and crisis period) we contemporarily account for the change in the regulatory environment.

8 Note that we substitute *CIR* by *ROE* (return on equity) as a more direct measure of bank performance during the robustness checks in Section 4.2 and Table 6.

observe a positive relationship between size and securitization. In contrast, if larger banks provide higher capital buffers and diversify loan portfolio risks more efficiently due to comparative advantages in providing credit monitoring services (Carletti and Hartmann, 2002; Demsetz and Strahan, 1997) and higher economies of scale and scope in general (Allen and Liu, 2007), larger banks are expected to be less engaged in the securitization business.

Market and country-specific determinants

To begin with, we employ the H-statistic (*H-statistic*) based on the model developed by Rosse and Panzar (1977) and Panzar and Rosse (1982, 1987) to control for banking market competition. The H-statistic is used by a wide range of empirical studies on banking market competition (e.g., Molyneux et al., 1994, Bikker and Haaf 2002, Claessens and Laeven 2004; Schaeck et al., 2009) since it allows for a direct measure of competitive conduct.[9] We follow the common approach to estimate H-statistic values and define a country's national border as the relevant market. However, with a special regard to Europe, we do not rely on balance sheet data from domestic banks only when estimating H-statistic values for each single country and year, but additionally employ data from foreign bank branches (including European foreign bank branches). Estimating the competition measure this way takes into account the contestability of European banking markets. To be more precise, it addresses the guaranteed free movement of capital (through foreign bank branches) within the EU (Article 56(1) of the EC Treaty) as well as the introduction of the ‘‘Single Banking License” from 1997 in Europe which allows a bank licensed in one European country to open as many branches as it wishes anywhere in the European community. Referring to theoretical

[9] As discussed in several relates studies (Cetorelli, 1999; Claessens and Laeven, 2004; Gutiérrez de Rozas, 2007; Schaeck et al., 2009; Bikker et al. 2009) the H-statistic is considered to be superior to other proxies for competition. This is due to the fact that the H-statistic is derived from bank-level data and accounts for bank-specific differences. A detailed empirical specification to estimate H-statistic values is given in the Appendix B.

predictions from Section 2.2, we expect a positive sign of the H-Statistic variable indicating that fiercer banking market competition should have a positive impact on a bank's securitization activity.

Furthermore, the slope of the yield curve (*Yield curve*) is employed to control for the impact of economic growth on a bank's decision to securitize. The yield curve is a well-accepted leading indicator for future prospects of the economy (Estrella and Gikas, 1991; Wheelock and Wohar, 2009; Adrian et al., 2010). Taking into account theoretical arguments, we expect banks in faster growing economies to stronger participate in the securitization market (Maddaloni and Peydró, 2011; Dell'Ariccia et al., 2012).

Finally, we include the log of a country's GDP (*GDP*) as a well-accepted macroeconomic control variable for the state of the economy to examine differences in numbers and volumes of securitization transactions due to national characteristics.

3.2. Empirical model

We employ a random effects Tobit regression model on panel data in order to investigate the determinants of a bank's decision on *how much* to securitize.[10] The Tobit framework accounts for the constrained range of the dependent variable and hence, is an econometrically sound choice to obtain consistent estimates of the regression coefficients (Minton et al., 2004; Affinito and Tagliaferri, 2010). The regression model is specified as

$$y_{it}^* = \mathbf{x}_{it}'\boldsymbol{\lambda} + \delta_i + u_{it}, \quad \text{with} \quad y_{it} = \begin{cases} y_{it}^* & \text{if } y_{it}^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

10 We additionally employ a Logit regression model on our panel data (see also Calomiris and Mason, 2004; Affinito and Tagliaferri, 2010). Since this model produces results of the same quality, we do not separately discuss the results in the following but provide a model description and respective results in the Appendix B.

where y^* is a latent variable that is observed for values greater than 0 corresponding to bank *i*'s total amount of securitized loans relative to total assets per year *t* and zero otherwise.[11] $\boldsymbol{\lambda}$ is a vector of coefficients associated with the regressor vector $\mathbf{x}_{it}$ including the explanatory variables as described in Section 3.1.2 on an annual basis. δ_i measures the individual effect and μ_{it} is the error term.[12]

Compared to related studies employing a cross-sectional or pooled approach, our panel model specification allows for both between and within variation in the data as well as unobservable heterogeneity across banks. The choice of the random effects model is appropriate for several reasons. *First*, since all relevant determinants of securitization are included in the regression specification, it is assumed that a possible correlation between the individual effects and the regressors can be ignored (e.g., Affinito and Tagliaferri, 2010). *Second*, even non-time varying determinants can be employed for the analysis. *And third*, the selection of a random effects approach is in line with the majority of related studies and therefore allows for a better comparison between our empirical results and those of the existing literature (Martín-Oliver, 2007; Affinito and Tagliaferri, 2010; Cardone-Riportella et al., 2010).[13]

We set time dummies to control for time-specific effects (e.g., trends in banking regulation; common shocks to the European banking market) in all model specifications. All bank-specific regressors enter the regression lagged by one period to address potential

11 As discussed in Section 3.1.1., volumes of multiple securitization transactions by one respective bank in one respective year were cumulated and subsequently included in the Tobit regression model whereas banks that did not securitize at all during the sample period were included with a transaction volume of zero.

12 The random-effects Tobit model on panel data uses the maximum likelihood estimation technique. The high-dimension integrals, that are part of the likelihood function of this model, are approximated by the Gauss-Hermite quadrature method. The Gauss-Hermit quadrature method is one of the most accepted approaches to approximate the maximum likelihood function of the estimators since it remarkably reduces the computational burden (Butler and Moffitt, 1982).

13 Moreover, the Hausman Test does not reject the null hypothesis of no correlation between the individual specific effect and the independent variables.

endogeneity problems. Similarly, to mitigate simultaneity and to capture probable delays in the impact of the economic development, we employ the one-period lagged yield curve.[14] We also control for possible multicollinearity issues between our independent variables in all model specifications. Thus, as the variance inflation factor (VIF) of all variables is close to 1 and the index of condition close to 2, we rule out that estimates are biased by collinearity among the determinants. Finally, while several banks in our sample continuously securitize over the entire sample period and others do not, we address heterogeneous securitization frequencies by clustering standard errors at the bank-level (Michalak and Uhde, 2011).

4. Empirical results

Baseline results from Tobit regressions are presented in Table 3 and include the entire sample period, the pre-crisis and the crisis period. We directly focus on the pre-crisis and crisis period when providing and discussing results from robustness checks (Tables 4-6) and sensitivity analyses (Tables 7-9). The correlation matrix is displayed in Table 10.

4.1. Baseline results

Entire sample period

Baseline results from Table 3 suggest that entering the securitization market by European banks is a composite decision based on bank-specific as well as market- and country-specific determinants.

As regards bank-specific determinants, regression specification (1) in Table 3 indicates that larger and less liquid European banks may have a higher propensity to securitize and

[14] Regression specifications with alternative lag structures and respective regression results are provided in Section 4.2.

may securitize to a higher extent.[15] Results correspond to empirical findings provided by Bannier and Hänsel (2008) and reveal that securitization is also employed as an alternative funding source. Furthermore, results at hand suggest that banks exhibiting higher loan loss reserves (a lower portfolio quality and hence, a higher exposure to credit risk) are less prone to securitize which corresponds to earlier empirical evidence provided by DeMarzo and Duffie (1999) and Calem and Lacour-Little (2004). Our finding that more risky banks securitize less, might be explained by the fact, that more risky banks have to provide higher explicit and implicit recourse to overcome possible information asymmetries with external investors when issuing securitization transactions (Gorton and Souleles 2006).

Turning to the market- and country-specific determinants, empirical results show that both, the competition and the yield curve measure, enter the regression model significantly positive. The positive impact of competition on securitization supports theoretical predictions that banks increase risky lending under fiercer banking market competition and thus securitize more in order to gain from portfolio diversification and specification. The positive impact of economic growth on securitization is in line with empirical results provided by Bannier and Hänsel (2008). Results suggest that an increase in the demand for loans during economic growth periods fosters securitization activity by banks. This might be due to the fact that the liquidity inflow from issuing securitization transactions is primarily used to fund new loans for new (and more risky) borrowers (Adrian et al., 2010; Maddaloni and Peydró, 2011).

Pre-crisis period

As mentioned in Section 3.1., the entire sample period reflects the boom phase of securitization transactions in Europe as well as the remarkable decrease in securitizations

[15] Note that we also refer to findings from Logit regressions (Table B1 in the Appendix B) when we interpret our baseline results in the following.

during the financial crisis period. Hence, it is imperative to investigate if significances and signs of the determinants differ during these time periods. In order to control for this aspect, we split our entire sample period into two sub periods ranging from 1997 to 2007 (*pre-crisis period*) and from 2008 to 2010 (*crisis period*). The strategy to analyze both periods separately avoids potential biases in our estimates and allows further disentangling of securitization determinants before and during the crisis.[16]

As Table 3, regression specification (2) indicates, results from *the pre-crisis period* generally confirm findings from the entire sample period with two exceptions. *First*, the liquidity measure is no longer statistically significant suggesting that liquidity shortages of European banks may have played only a minor role during the pre-crisis period due to a well-functioning interbank market. *Second*, the cost-income-ratio enters the regression significantly negative indicating that more efficient and better performing banks may securitize to a higher extent. Our finding is in line with Lockwood et al. (1996) and supports the “risk-appetite”-argument provided by Hänsel and Krahnen (2007). Consequently, especially banks with an efficient risk management and a comparatively high performance tend to stronger engage in the securitization business until the financial crisis.

Crisis period

Turning to the crisis period empirical results at hand paint a rather different picture. Compared to the entire period, we observe a significant coefficient of bank size and liquidity measure only. This result is expected for two reasons. *First*, the melt-down in the subprime

[16] The choice of the respective sub periods is supported by descriptive statistics as presented in Figure 1 and by results from a Chow- and CUSUM-test. From an economic point of view, defining the period from 2008 to 2010 as the crisis period is rational since most of the market assessments by European banks are observed during this period (BIS, 2012). Moreover, almost all countries in our sample experienced a banking crisis during this period as suggested by the “Systemic Banking Crises Database” provided by Leaven and Valencia (2012).

mortgage market and the resulting confidence crisis within the financial sector led to a freezing up of the interbank market and hence, to a severe liquidity crisis for the entire banking sector in Europe (Brunnermeier, 2008). *Second*, securitization is primarily used as collateral during repo-transactions with the European Central Bank (ECB) in order to compensate liquidity shortages in banks during the crisis period (Carbó-Valverde et al., 2011). As stated by the ECB (2011), a switch from the former "originate-to-distribute" model of securitization to a more liquidity-dominated "originate-to-repo" approach is observed during the crisis period.

4.2. Robustness checks

First, we employ different lag structures and an average measure of the competition variable to control for possible endogeneity problems in our model specification. Regression specifications (1a)-(2c) in Table 4 indicate that our baseline finding of a positive impact of fiercer competition on securitization during the pre-crisis period is reiterated even when using alternative lag structures of the competition variable. Moreover signs and significances of all other determinants remain robust throughout all regressions. Hence, we rule out that baseline results are driven by possible endogeneity issues related to a misspecification of the competition measure.

Second, we substitute *LL Reserves* by the z-score (*z-score*), the volatility of its stock returns (*Vola*) and the distance-to-default (*DtD*) as alternative accounting and market-based measures of a bank's *overall* risk exposure in Table 5.[17] As regression specifications (1a)-(2c) show, the z-score as well as the distance-to-default variable enter respective regressions with

[17] We use an average volatility of stock returns based on a one-year time horizon. Moreover, we address possible reverse causality between bank risk and securitization by including one-period lags of all alternative risk measures. Further details concerning the calculation of the distance-to-default measure and the z-score are provided in the Appendix B.

a positive sign whereas the measure of the volatility of stock returns exhibits a negative sign. However, alternative risk measures are statistically insignificant for both sample periods while findings from further determinants remain robust. Thus, we rule out that our results are biased by any other risk factor beyond credit risk. Furthermore, our results correspond to findings provided by Minton et al. (2004) suggesting that especially banks with higher costs of financial distress did not securitize to a higher extent in the years before and during the crisis.

Third, following Affinito and Tagliaferri (2010) and Cardone-Riportella et al. (2010) we control for the robustness of the bank-specific measures in a next step. Accordingly, we substitute (a) the variable “Liquidity” with a bank’s liquid assets (*Liquid Assets*) as a different proxy for a bank’s liquidity position, (b) the variable “LL Reserves” with the ratio of a bank’s impaired loans to gross loans (*NPL*) as an alternative proxy for a bank’s credit risk exposure, (c) the variable “Tier1” with the ratio of a bank’s total equity to total assets (*Equity Share*) as a different proxy for the capital environment and (d) the variable “CIR” with a bank’s return on equity (*ROE*) as an alternative and more direct proxy for bank performance.

Regression models are estimated step-by-step. As shown by regressions (1a)-(1d) and (2a)-(2d) in Table 6, alternative specifications of a bank’s exposure to credit risk (*NPL*) and bank performance (*ROE*) enter regression specifications (1b) and (1d) significantly negative and positive during the pre-crisis period respectively. Moreover, the liquidity proxy enters regression specification (2a) significantly negative during the crisis period. Thus, while signs and significances of all other determinants remain robust throughout all regression specifications, baseline findings from Table 3 are reiterated for the sub periods even when employing alternative proxies of bank-specific determinants.

Fourth, as the relationship between the bank size variable and the further four bank-specific determinants in our model setup may raise concerns about simultaneity, we account for this issue by including a two-period lagged variable of bank size. As shown by specifications (1e) and (2e) in Table 6, bank size enters respective regression significantly positive confirming our findings from baseline regressions in Table 3. Moreover, as all other determinants remain robust for the pre-crisis and crisis period, we rule out that our baseline results are driven by simultaneity issues.

4.3. Sensitivity analyses

4.3.1. Determinants based on the transaction type

As discussed in Section 3.1.1 our sample of loan securitizations consists of true sale and synthetic transactions. Although the difference in means of the value of true sale and synthetic securitizations is small, the total number of true sale transactions is more than twice as high compared to the number of synthetic transactions (Table 2a). Accordingly, as the impact of securitization determinants might differ depending on different transaction types, we build two subsamples of true sale and synthetic securitization transactions and reinvestigate the effects of the securitization determinants employed.

As shown in Table 7, empirical results initially reveal that the statistical impact of single determinants on securitization does not remarkably differ between both subsamples and time periods. As regards the *pre-crisis period*, the significant effect of bank size, competition and the yield curve measure remain robust for both subsamples compared to our baseline regressions. However, we observe a significantly negative effect of bank risk and performance only for the subsample of true sale transactions. These findings support the common belief that securitizations of high-quality loan portfolios can mitigate information asymmetries between the originating bank and less informed external investors resulting in a fully compensated risk transfer (Gorton and Souleles, 2006). Turning to the cost-income-ratio, empirical findings from Table 7 support the accounting-gains-hypothesis proposing that issuing true sale transactions with market values above actual book values provokes accounting gains (Ambrose et al. 2005; Karaoglu, 2005). Moreover and as already discussed, especially banks with an efficient risk management are more prone to profit from this advantage which might explain the negative sign of the cost-to-income measure.

Turning to the *crisis period* the liquidity measure exhibits a significantly negative sign only for the subsample of true sale regressions. The reason is that (1) liquidity effects from securitization can only be realized by means of true sale transactions and (2) the ECB required a true sale structure for any repo transaction that served to compensate liquidity shortages in banks during the crisis period.

4.3.2. Determinants based on the underlying asset portfolio

Following Uzun and Webb (2007) and Cardone-Riportella et al. (2010) we additionally control for the impact of differences in the underlying asset pool of a securitization transaction. More specifically, as some determinants of a securitization transaction may be related to the visibility of the respective underlying loan portfolio (Panetta and Pozzolo, 2010), we distinguish between informationally opaque securitization transactions (CDO) and less-opaque transactions (including credit card, mortgage and consumer loans). The selection of the respective subsamples is motivated by the fact, that securitizations from the less-opaque sample are based on loans with a high degree of standardization, collateralization and granularity. In contrast, the opaque securitization sample is characterized by a high number of complex loan arrangements which are typically difficult to value for potential investors.

Regression results from Table 8 generally indicate that securitization determinants differ between both subsamples. In particular, the level of a bank’s risk exposure and performance as well as the degree of banking market competition and economic growth exhibit different effects during the *pre-crisis period*.

To begin with, as shown in Table 8 a higher level of loan loss reserves and hence, a higher exposure to credit risk tends to be an obstacle to the securitization of non-opaque assets. This result was expected since the securitization of less risky loans does not require “a hiding of credit risk”. Additionally, transparent securitization transactions including less risky underlyings should favor the originating bank’s reputation when entering the securitization market repeatedly. Furthermore, a significantly positive impact of an increase in banking market competition on the securitization of non-opaque (less risky) underlyings is in line with theoretical predictions proposed by Hakenes and Schnabel (2010). They suggest that fiercer competition reduces the bank’s risk bearing capacity and forces a bank to securitize even less risky and more transparent loans.

Turning to the subsample of securitization transactions including opaque underlyings, empirical results initially reveal that banks with a more efficient risk management system may be more prone to engage in the securitization of less transparent (more risky) loans. These findings suggest that banks with greater risk management expertise and hence, advantages in the pricing of complex loan portfolios, may indeed exploit their competitive advantage and (additionally) securitize even opaque asset portfolios.

As regards country-specific determinants, we find a positive impact of economic growth on the securitization of opaque assets which can be explained by the fact that banks tend to reduce their lending standards and monitoring efforts under fiercer competition (Maddaloni and Peydró, 2011; Dell’Ariccia et al., 2012). In turn, the securitization of less transparent (and more risky) loan arrangements is more likely in competitive markets.

Considering the *crisis period* we find that banks with a greater risk management expertise may be more prone to issue securitization transactions with less transparent underlyings. Furthermore, we provide evidence that a weak liquidity position prompts banks to stronger engage in the securitization of non-opaque assets during the crisis period. This result supports findings from baseline regressions suggesting that securitization during the crisis period is primarily used as a collateral for repo-transactions with the ECB, which specified extensive quality requirements with regard to this collateral.

4.3.3. Determinants based on the institutional framework

We finally examine if differences in the institutional framework may affect a bank's decision to securitize. The institutional framework comprises a country's de facto implementation of the regulatory and supervisory environment as proposed by Basel II as well as a measure of the development of the capital market. Single components of the institutional framework are proxied by well-accepted measures from the banking and finance literature (Table 1). Variables are obtained from the World Bank Surveys on Bank Regulation and Supervision (Barth et al. 2008, 2013) as well as the 2009-revised Financial Structure Dataset provided by the World Bank.

We initially control for the effect of the supervisory official supervisory power (*OSP*) which accounts for the strength of supervisory authorities and their ability to take legal action against banks to prevent and overcome financial fragility within the financial sector. Higher values of this measure indicate greater supervisory power. As specifications (1a) and (2a) in Table 9 report, supervisory power enters both regressions significantly positive indicating that banks being closely monitored by supervisors are more prone to securitize higher volumes of credit risk during the pre-crisis and crisis period. Results suggest that greater supervision may force banks to more efficiently manage their credit risk exposures, e.g. by means of transferring risks to external investors through securitization.

Alongside the supervisory framework, we employ the capital regulatory index (*Capstring*) to control for a country's banking regulatory environment in a next step. This index measures the regulatory requirements concerning a bank's equity capital that is used to back risks.

Higher values of this index indicate greater capital stringency. As shown, the capital regulatory index enters regression specifications (1b) and (2b) significantly positive indicating that stronger capital stringency may foster securitization activities during the pre-crisis and crisis period. We suggest that higher capital requirements encourage (or even force) banks to transfer credit risks out of their balance sheets through securitization in order to save regulatory equity capital and hence, decrease opportunity costs.

Finally, we investigate the impact of the development of a country's capital market on securitization activities by European banks. We employ a measure of stock market capitalization (*SMC*), which is calculated as the ratio of the value of listed shares to deflated GDP. As specification (1c) reports, stock market capitalization enters the regression significantly positive indicating that banks in more developed capital markets may securitize to a higher extent during the pre-crisis period. Our result supports theoretical arguments that markets with a broader and more experienced investor basis may provoke a higher demand for structured finance products. The latter is due to the fact that sophisticated investors are in a better position to assess the related risk-return profiles from a securitization transaction. In contrast, we do not provide any empirical evidence for an impact of stock market development on securitization during the crisis period. This result was expected and might be explained by the rapid withdrawal of investors from the securitization market due to an abruptly decreasing market confidence in the aftermath of the financial crisis.

5. Conclusion

Analyzing 75 securitizing and non-securitizing stock-listed banks in the EU-13 plus Switzerland over the period from 1997 to 2010, this paper provides empirical evidence that loan securitization in Europe is triggered by bank-specific as well as market- and country-specific determinants. As regards bank-specific determinants, we find that larger banks, exhibiting a lower exposure to credit risk along with a higher performance are more prone to enter the securitization market and issue larger transaction volumes during the years before the financial crisis. In contrast, empirical results also indicate that securitization is mainly driven by the banks' need for liquidity during the crisis period. Turning to market- and country-specific determinants, we find that banks operating in European countries with fiercer banking market competition and higher economic growth tend to stronger engage in the securitization business during the crisis period. Finally, results from several subsample regressions reveal that determinants of loan securitizations in Europe depend on the transaction type, the underlying asset portfolio and the regulatory and institutional environment.

Against the background of the empirical results, we derive the following policy implications. Providing evidence that especially a lower credit risk exposure induces securitization by European banks until the financial crisis, we suggest that only less risky banks with a higher loan portfolio quality are in fact able to transfer risk and are therefore securitizing during this period. Thus, as most banks have to retain the risky first-loss piece of a securitization transaction to serve as a quality signal towards external investors, this may hamper an efficient transfer of credit risk. Hence, a more transparent securitization design could reduce possible "lemons discounts" and allow even more risky banks to engage in the loan securitization business.

Accordingly, our results support recent regulatory and industry initiatives provided by the Prime Collateralised Securities (PCS) and True Sale Initiative (TSI) that focus on an increase in transparency and standardization levels for the European securitization market (ECB, 2011; BCBS, 2012). In particular, establishing a standardized securitization platform would also entice less experienced and smaller institutions to enter the market for structured finance products since results at hand suggest that the securitization business in Europe is primarily used by comparatively larger banks with a more efficient risk management. However, keeping in mind that securitization is commonly accepted as one of the main triggers of the global financial turmoil, the revitalization of the European securitization market through standardization and transparency must definitely involve recent proposals by the European Commission and the European Investment Bank. These proposals aim to promote the re-launch of the securitization business in Europe under much sounder conditions.

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Appendix A

Table 1
Notes on variables and data sources

Variable	**Proxy**	**Description**	**Data Sources**
Dependent variables			
Secvol	Securitization	Ratio of a banks' cumulated securitization volume per year to total assets.	Moody's, Standard & Poor's and FitchRatings, BankScope
Sec		Dummy that takes on the value of 1 in years when a bank completes a securitization transaction and 0 otherwise.	
True sale		Ratio of a banks' cumulated volume of true sale securitizations per year to total assets.	
Synthetic		Ratio of a banks' cumulated volume of synthetic securitizations per year to total assets.	
Non-Opaque		Ratio of a banks' cumulated volume of securitizations per year to total assets while the underlying securitization portfolio is based on consumer, mortgage as well as credit card backed securities.	
Opaque		Ratio of a banks' cumulated volume of securitizations per year to total assets while the underlying securitization portfolio is based on collateral debt obligations (CDOs) and other unspecified assets.	
Explanatory variables			
Bank-specific			
Liquidity	Liquidity / Funding	Ratio of the accounting value of a bank's liquid assets to deposits and short-term funding per year.	BankScope
Liquid assets		Accounting value of a bank's liquid assets per year. Build as 1minus the ratio of net loans to total assets.	
LL Reserves	Risk exposure	Ratio of the accounting value of a bank's loan loss reserves to gross loans per year.	
NPL		Ratio of the accounting value of a bank's impaired loans to gross loans per year.	
Tier1	Capital environment	Ratio of the accounting value of a bank's Tier1 capital to risk weighted assets per year.	
Equity Share		Lag (1) of the ratio of the accounting value of a bank's total equity to total assets per year.	
CIR	Performance	Accounting value of a bank's cost-income-ratio per year.	
ROE		Accounting value of a bank's return on equity before taxes per year.	
Size	Bank size	Accounting value of the bank's total assets per year.	
Market-specific			
H-statistic	Competition	Measure of the degree of banking market competition per country and year. H-Statistic is estimated cross-sectionally on a bank-level. Higher values indicate more competitive banking markets. Further details are provided in the Appendix B.	BankScope, own calc.
Country-specific			
Yield curve	Economic growth	Slope of the yield curve. Calculated as 10-year minus 2-year government bond yields per country and year.	Datastream
GDP	State of the economy	The natural log of a country's GDP in constant EUR per year.	World Bank's WDI

Table 1 (cont.)

Variable	Proxy	Description	Data Sources
Alternative risk measures			
z-score		Natural log of a bank's ratio of the sum of equity capital to total assets and the return on average assets before taxes (ROAA) to the standard deviation of ROAA per year. The standard deviation of ROAA is calculated employing a five-year rolling window.	BankScope, own calc.
Vola	Risk exposure	A banks' stock return volatility per year.	BankScope, Datastream own calc.
DtD		A bank's distance-to-default per year. The distance to default is calculated following the Merton framework (1973, 1974). Further details are provided in the Appendix B.	Datastream, own calc.
Regulatory and institutional environment			
OSP	Regulatory environment	Yearly index that measures the extent to which official supervisory authorities have the authority to take specific actions to prevent and correct problems. The index combines the following official supervisory oversight design features: Prompt corrective power, restructuring power, declaring insolvency power. The index ranges from 0 to 13, with higher index values indicating a higher degree of official supervisory oversight.	Barth et al. (2008, 2013)
Capstring		Yearly index of capital regulation that measures the extent to which the source of funds that count as regulatory capital can include assets other than cash or government securities, borrowed funds, and whether the sources of capital are verified by the regulatory or supervisory authorities.	
SMC	Institutional environment	Proxy for capital market development. Stock market capitalization is calculated as the ratio of the value of listed shares to deflated GDP per country and year.	World Bank

Table 2a
Descriptive statistics of securitization transactions in the sample (in billion €)

	N	**Total Volume**	**Mean**	**Standard Deviation**	**5% percentile**	**95% percentile**
Total						
True sale Transactions	668	1.387	2.076	2.811	0.200	7.092
Synthetic Transactions	282	0.713	2.527	2.870	0.280	8.280
Total Transactions	*950*	*2.099*	*2.210*	*2.835*	*0.205*	*7.415*
Underlying asset pool						
Collateralized Debt Obligations	293	0.653	2.230	2.576	0.225	8.280
Residential Mortgage Backed Securities	419	1.210	2.887	3.410	0.263	8.174
Commercial Mortgage Backed Securities	90	0.093	1.029	1.153	0.286	3.930
Credit Cards Receivables	24	0.029	1.203	1.908	0.112	1.658
Consumer Loans	59	0.050	0.840	0.839	0.41	1.900
Others	65	0.065	0.998	0.764	0.140	2.500
Total Transactions	*950*	*2.099*	*2.210*	*2.835*	*0.205*	*7.415*

Table 2b
Descriptive statistics

Variable	N	Mean	Std. dev.	5% percentile	95% percentile
Secvol	1,050	0.23	0.31	0	0.73
Sec	1,050	0.38	0.48	0	1
True sale	1,050	0.18	0.29	0	0.71
Synthetic	1,050	0.09	0.22	0	0.65
Non-Opaque	1,050	0.17	0.28	0	0.71
Opaque	1,050	0.12	0.24	0	0.65
LL Reserves	832	2.40	1.68	0.29	5.69
NPL	713	2.72	2.33	0.38	7.23
Liquidity ratio	899	33.44	24.40	8.74	91.86
Liquid Assets	899	5.38	2.81	2.17	10.53
CIR	894	61.68	13.14	38.94	84.96
ROE	899	14.24	11.37	-11.65	29.34
Tier1	864	8.19	1.93	5.62	11.74
Equity share	899	5.22	2.28	2.17	9.02
Size	899	11.64	1.43	9.26	13.86
H-statistic	985	0.43	0.19	0.12	0.77
Yield curve	876	1.00	0.63	0.09	2.09
GDP	1,041	13.71	0.82	11.96	14.65
z-score	895	19.12	12.31	4.35	47.66
Vola	822	0.29	0.11	0.14	0.49
DtD	761	3.92	1.35	2.00	6.54
OSP	1,050	-0.58	0.88	-1.80	0.90
Capstring	1,050	1.84	0.79	1	3
SMC	1,050	0.87	0.55	0.16	1.81

Figure 1
Development of the number of securitization transactions per year

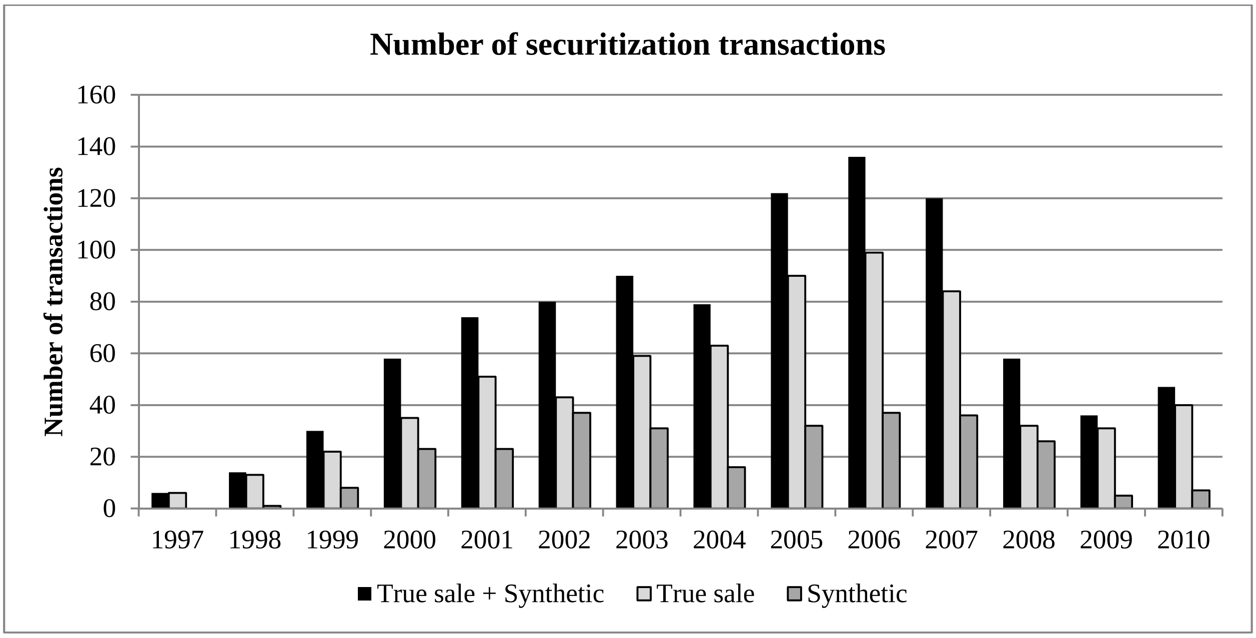


Figure 2
Development of the volume of securitization transactions per year

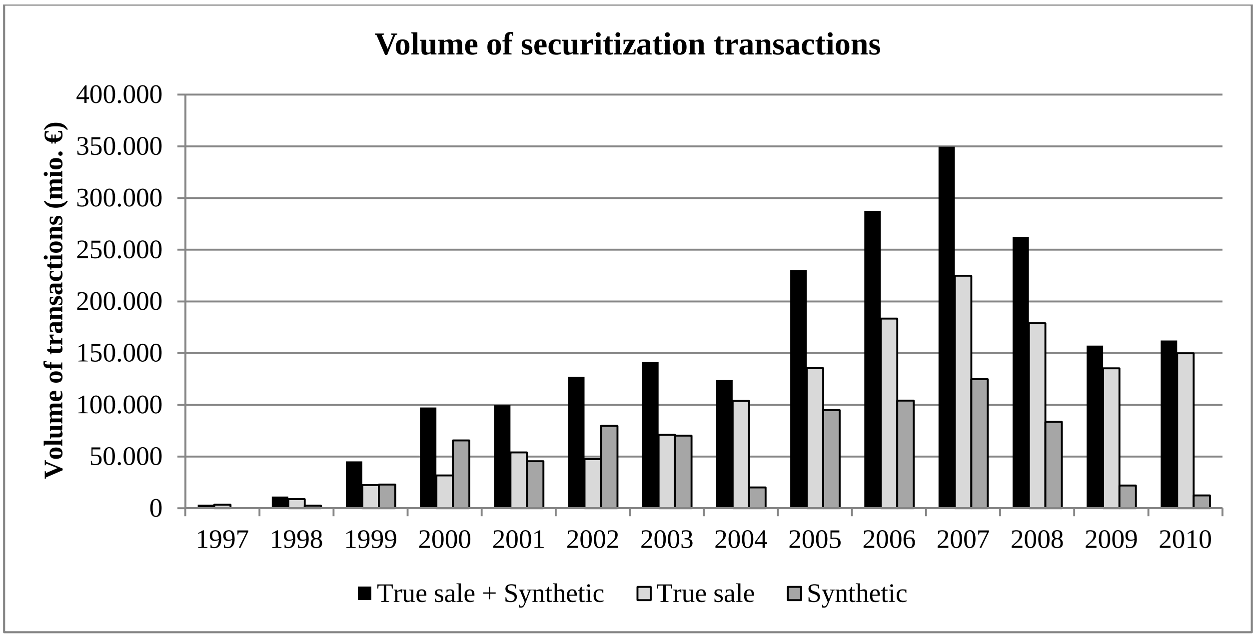
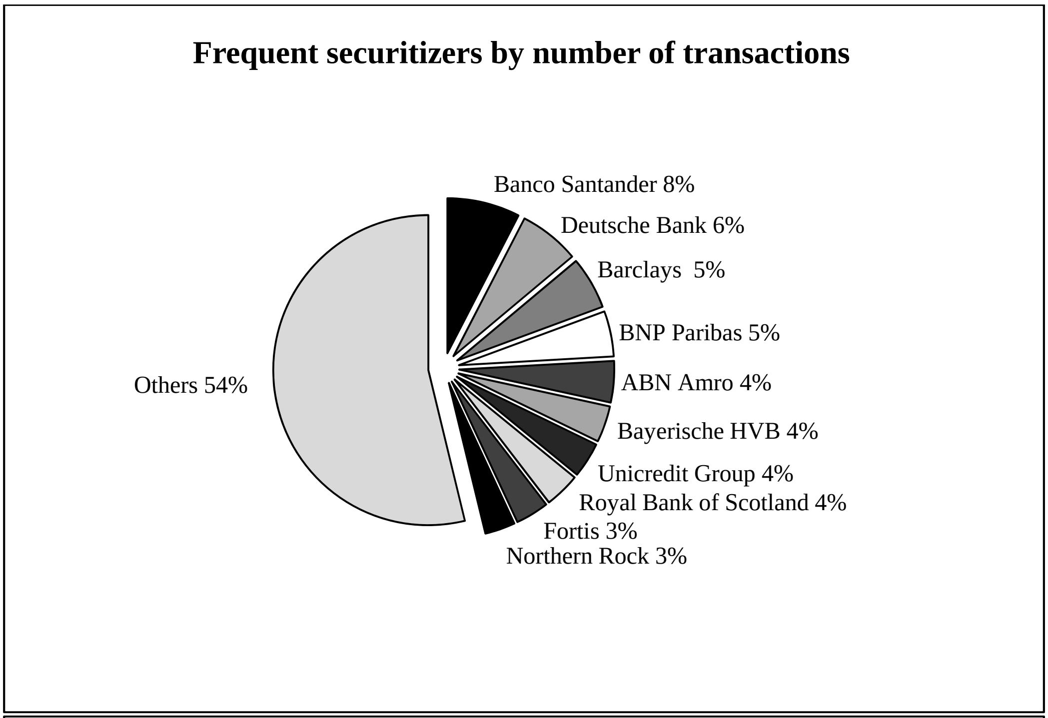


Figure 3
Frequent securitizers by the number and volume of securitization transactions



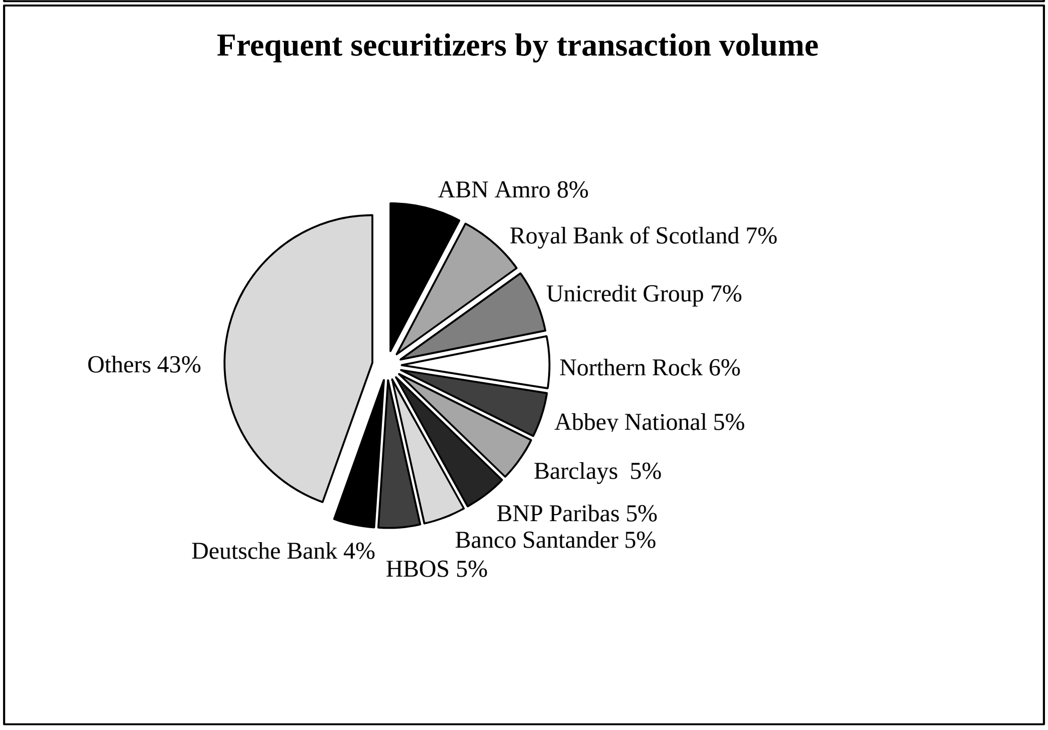


Figure 4
Percentage of sample banks that engaged in the securitization business per year

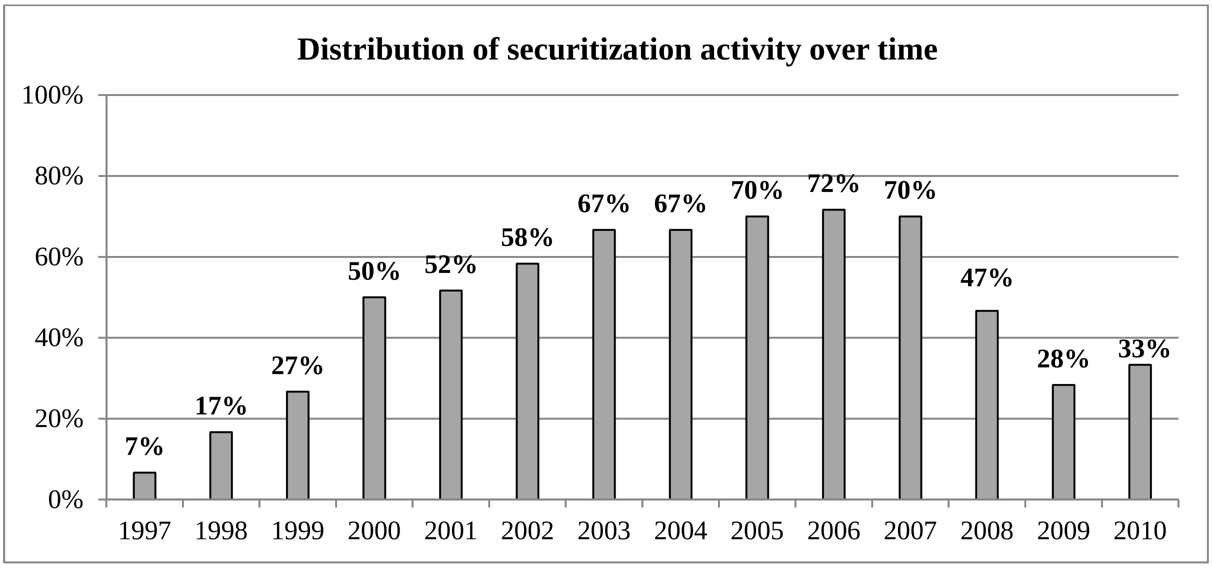


Table 3
Baseline regressions

	Secvol (full sample) (1)	Secvol (pre-crisis) (2)	Secvol (crisis) (3)
Liquidity $_{(t-1)}$	-0.004**	-0.002	-0.012**
	(0.042)	(0.401)	(0.016)
LL Reserves $_{(t-1)}$	-0.063**	-0.062**	0.063
	(0.042)	(0.039)	(0.362)
Tier1 $_{(t-1)}$	-0.006	-0.023	0.015
	(0.779)	(0.402)	(0.765)
CIR $_{(t-1)}$	-0.005	-0.010**	0.000
	(0.168)	(0.017)	(0.986)
Size $_{(t-1)}$	0.189***	0.152***	0.335***
	(0.000)	(0.000)	(0.000)
H-statistic	0.294**	0.426***	-0.317
	(0.028)	(0.001)	(0.520)
Yield curve $_{(t-1)}$	0.298**	0.226**	0.314
	(0.018)	(0.044)	(0.179)
GDP	0.098	0.098	0.055
	(0.273)	(0.267)	(0.719)
Const.	-3.48**	-2.60*	-4.74**
Cluster bank-level	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
N	698	521	177
Log likelihood	-430.74	-309.34	-102.88
LR test	122.52***	98.31***	36.32***
Pseudo R^2	0.13	0.14	0.15

The Tobit panel model estimated is Secvol $_{(i=bank,\ t=time)}$ = λ_1 Liquidity$_{i,t-1}$ + λ_2 LLReserves$_{i,t-1}$ + λ_3 TIER1$_{i,t-1}$ + λ_4 CIR$_{i,t-1}$ + λ_5 Size$_{i,t-1}$ + λ_6 H-statistic$_{i,t}$ + λ_7 Yield curve$_{i,t-1}$ + λ_8 GDP$_{i,t}$ + δ_i + $u_{i,t.}$ Variables are incuded on a yearly basis. The dependent variable is the securitization volume to total assets per bank *i* and year *t*. Except *GDP* all explanatory variables are lagged by one period. Regression specification (1) refers to the entire sample period from 1997 to 2010. Specification (2) includes the pre-crisis period (1997-2007) whereas specification (3) refers to the crisis period (2008-2010). p-values are in parenthesis. ***, **, *: indicate statistical significance at the 1%, 5% and 10% level..

Table 4
Robustness checks: Alternative competition variable structures

	Secvol (pre-crisis)			Secvol (crisis)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
H-statistic $_{(t-1)}$	0.447***			-0.284		
	(0.005)			(0.518)		
H-statistic $_{(t-2)}$		0.344**			0.582	
		(0.021)			(0.112)	
H-statistic $_{(3Y\text{-}average)}$			0.755**			0.952
			(0.015)			(0.151)
Liquidity $_{(t-1)}$	-0.001	-0.001	-0.000	-0.012***	-0.012**	-0.012**
	(0.553)	(0.576)	(0.899)	(0.010)	(0.011)	(0.011)
LL Reserves $_{(t-1)}$	-0.069**	-0.071**	-0.062**	0.054	0.085	0.101
	(0.023)	(0.022)	(0.047)	(0.438)	(0.221)	(0.183)
Tier1 $_{(t-1)}$	-0.032	-0.036	-0.016	0.014	0.009	0.004
	(0.251)	(0.211)	(0.633)	(0.779)	(0.849)	(0.939)
CIR $_{(t-1)}$	-0.011**	-0.011**	-0.012**	0.000	-0.002	-0.003
	(0.017)	(0.016)	(0.013)	(0.984)	(0.666)	(0.545)
Size $_{(t-1)}$	0.150***	0.153***	0.133***	0.342***	0.326***	0.316***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Yield curve $_{(t-1)}$	0.274**	0.210*	0.221*	0.265	0.388	0.498*
	(0.019)	(0.068)	(0.074)	(0.323)	(0.107)	(0.068)
GDP	0.092	0.077	0.080	0.026	0.101	0.142
	(0.280)	(0.362)	(0.356)	(0.851)	(0.405)	(0.255)
Const.	-2.43*	-2.03	-2.12	-4.36**	-5.45**	-5.99***
Cluster bank-level	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	515	515	457	179	179	179
Log likelihood	-309.34	-311.22	-277.74	-105.36	-104.37	-104.44
LR test	95.53***	91.77***	60.92***	36.46***	38.43***	38.30***
Pseudo R^2	0.13	0.13	0.10	0.15	0.16	0.16

The empirical model is defined in Table 3. Specifications (1a) and (2a) include the 1-year lagged H-statistic, specifications (1b) and (2b) the 2-year lagged H-statistic and specifications (1c) and (2c) include a three year average of the H-statistic.

Table 5
Robustness checks: Alternative risk measures

	Secvol (pre-crisis)			Secvol (crisis)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
z-score $_{(t-1)}$	0.001			0.007		
	(0.893)			(0.283)		
Vola $_{(t-1)}$		-0.221			-0.503	
		(0.654)			(0.539)	
DtD $_{(t-1)}$			0.011			0.004
			(0.741)			(0.960)
Liquidity $_{(t-1)}$	-0.002	-0.002	-0.001	-0.012**	-0.016***	-0.015***
	(0.366)	(0.435)	(0.496)	(0.012)	(0.000)	(0.000)
Tier1 $_{(t-1)}$	-0.014	-0.009	-0.009	0.014	0.034	0.025
	(0.489)	(0.709)	(0.723)	(0.770)	(0.445)	(0.556)
CIR $_{(t-1)}$	-0.009***	-0.009***	-0.009**	0.002	-0.000	-0.001
	(0.009)	(0.009)	(0.013)	(0.671)	(0.995)	(0.809)
Size $_{(t-1)}$	0.161***	0.165***	0.167***	0.326***	0.324***	0.318***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
H-statistic	0.380***	0.375**	0.372**	-0.245	-0.074	-0.054
	(0.008)	(0.013)	(0.014)	(0.596)	(0.866)	(0.903)
Yield curve $_{(t-1)}$	0.204**	0.190*	0.192*	0.331	0.309	0.310
	(0.049)	(0.076)	(0.074)	(0.125)	(0.139)	(0.141)
GDP	0.042	0.038	0.046	0.054	0.134	0.126
	(0.622)	(0.647)	(0.577)	(0.701)	(0.384)	(0.407)
Const.	-2.20	-2.25	-2.27	-4.73**	-5.48**	-5.31**
Cluster bank-level	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	570	520	517	180	163	163
Log likelihood	-340.84	-317.81	-315.60	-105.89	-92.62	-92.91
LR test	89.40***	79.48***	80.14***	37.88***	40.20***	39.62***
Pseudo R^2	0.12	0.11	0.11	0.15	0.18	0.18

The empirical model is defined in Table 3. LL Reserves is substituted by different accounting and market-based risk measures (z-score, volatility of bank stock returns and distance-to-default) in specifications (1a)-(1c) and (2a)-(2c).

Table 6
Robustness checks: Alternative bank-specific variable specification

	Secvol (pre-crisis)					Secvol (crisis)				
	(1a)	(1b)	(1c)	(1d)	(1e)	(2a)	(2b)	(2c)	(2d)	(2e)
Liquid Assets $_{(t-1)}$	-0.004					-0.022***				
	(0.250)					(0.007)				
NPL $_{(t-1)}$		-0.055***					-0.019			
		(0.008)					(0.651)			
Equity Share $_{(t-1)}$			-0.016					-0.018		
			(0.543)					(0.707)		
ROE $_{(t-1)}$				0.006*					0.008	
				(0.097)					(0.175)	
Size $_{(t-2)}$					0.146***					0.338***
					(0.000)					(0.000)
Liquidity $_{(t-1)}$		-0.001	-0.003	-0.003	-0.002		-0.011**	-0.011**	-0.013**	-0.012**
		(0.781)	(0.262)	(0.256)	(0.476)		(0.037)	(0.018)	(0.011)	(0.015)
LL Reserves $_{(t-1)}$	-0.055*		-0.068**	-0.047*	-0.064**	0.042		0.078	0.076	0.058
	(0.068)		(0.026)	(0.088)	(0.038)	(0.542)		(0.284)	(0.256)	(0.403)
Tier1 $_{(t-1)}$	-0.020	-0.020		-0.024	-0.027	0.015	-0.003		0.017	0.005
	(0.496)	(0.487)		(0.386)	(0.337)	(0.749)	(0.961)		(0.705)	(0.919)
CIR $_{(t-1)}$	-0.010**	-0.011**	-0.011***		-0.011**	0.005	-0.000	-0.001		-0.001
	(0.019)	(0.027)	(0.007)		(0.012)	(0.425)	(0.939)	(0.833)		(0.815)
Size $_{(t-1)}$	0.167***	0.146***	0.143***	0.149***		0.409***	0.326***	0.330***	0.343***	
	(0.000)	(0.000)	(0.002)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	
H-statistic	0.412***	0.414***	0.452***	0.412***	0.419***	-0.171	-0.327	-0.423	-0.015	-0.260
	(0.002)	(0.005)	(0.001)	(0.002)	(0.002)	(0.734)	(0.487)	(0.378)	(0.974)	(0.605)
Yield curve $_{(t-1)}$	0.220**	0.143*	0.234**	0.262**	0.224**	0.372	0.336	0.262	0.308	0.312
	(0.041)	(0.091)	(0.034)	(0.021)	(0.048)	(0.112)	(0.164)	(0.258)	(0.208)	(0.186)
GDP	0.079	0.095	0.107	0.103	0.099	0.034	0.076	0.041	0.091	0.069
	(0.348)	(0.282)	(0.206)	(0.257)	(0.264)	(0.828)	(0.618)	(0.780)	(0.554)	(0.657)
Constant	-2.43*	-3.45*	-2.75**	-3.35**	-2.48*	-5.17**	-4.65*	-4.23*	-5.51**	-4.78*
N	521	440	537	521	515	177	171	182	181	177
Log likelihood	-309.26	-256.89	-320.74	-313.94	-308.54	-103.80	-101.49	-105.39	-105.40	-102.91
LR test	98.48***	107.17***	89.76***	89.11***	96.34***	34.48***	34.89***	35.74***	39.13***	36.28***
Pseudo R^2	0.14	0.17	0.13	0.12	0.14	0.14	0.15	0.15	0.16	0.15

The empirical model is defined in Table 3. Bank-specific covariates are substituted by alternative proxies for liquidity (*Liquid Assets* in specifications (1a) and (2a)), risk exposure (*NPL* in specifications (1b) and (2b)), capital environment (*Equity Share* in specifications (1c) and (2c)), performance (*ROE* in specifications (1d) and (2d)), and size (*Lag (2) of the log of Total Assets* in specifications (1e) and (2e)).

Table 7
Sensitivity analyses: True sale vs. synthetic securitization transactions

	True sale (pre-crisis) (1a)	Synthetic (pre-crisis) (1b)	True sale (crisis) (2a)	Synthetic (crisis) (2b)
Liquidity $_{(t-1)}$	-0.003	-0.002	-0.013**	-0.006
	(0.261)	(0.531)	(0.038)	(0.209)
LL Reserves $_{(t-1)}$	-0.093**	-0.063	0.045	0.056
	(0.010)	(0.207)	(0.576)	(0.654)
Tier1 $_{(t-1)}$	-0.034	0.023	-0.038	0.053
	(0.331)	(0.587)	(0.502)	(0.579)
CIR $_{(t-1)}$	-0.009*	-0.011	0.004	-0.011
	(0.085)	(0.140)	(0.434)	(0.331)
Size $_{(t-1)}$	0.122**	0.369**	0.418***	0.273**
	(0.015)	(0.019)	(0.000)	(0.023)
H-statistic	0.330**	0.385*	-0.405	-0.568
	(0.026)	(0.077)	(0.509)	(0.432)
Yield curve $_{(t-1)}$	0.203*	0.362**	0.540	0.351
	(0.098)	(0.027)	(0.122)	(0.433)
GDP	0.091	0.229*	0.046	0.011
	(0.449)	(0.076)	(0.749)	(0.965)
Const.	-2.17	-7.97***	-5.73**	-3.81
Cluster bank-lever	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
N	521	521	177	177
Log likelihood	-292.69	-230.26	-85.36	-63.00
LR test	68.44***	68.79***	35.99***	16.18*
Pseudo R^2	0.11	0.13	0.17	0.11

The empirical model is defined in Table 3. The ratio of the volume of true sale securitization transactions to total assets is included as the dependent variable in specifications (1a) and (2a) respectively. The ratio of the volume of synthetic securitization transactions to total assets is employed as the dependent variable in specifications (1b) and (2b) respectively.

Table 8
Sensitivity analyses: Non-opaque vs. opaque transactions

	Non-opaque (pre-crisis) (1a)	Opaque (pre-crisis) (1b)	Non-opaque (crisis) (2a)	Opaque (crisis) (2b)
Liquidity $_{(t-1)}$	-0.000	-0.002	-0.014**	-0.006
	(0.952)	(0.579)	(0.019)	(0.125)
LL Reserves $_{(t-1)}$	-0.134***	0.012	0.055	0.088
	(0.000)	(0.741)	(0.525)	(0.478)
Tier1 $_{(t-1)}$	-0.017	-0.050	0.030	0.043
	(0.591)	(0.219)	(0.648)	(0.626)
CIR $_{(t-1)}$	-0.006	-0.017***	0.001	-0.012*
	(0.143)	(0.004)	(0.833)	(0.083)
Size $_{(t-1)}$	0.099*	0.247***	0.404***	0.322***
	(0.076)	(0.000)	(0.000)	(0.003)
H-statistic	0.551***	0.101	-0.087	-0.623
	(0.001)	(0.680)	(0.891)	(0.357)
Yield curve $_{(t-1)}$	0.231	0.370***	0.564	0.355
	(0.142)	(0.008)	(0.101)	(0.262)
GDP	0.117	0.079	0.141	-0.032
	(0.325)	(0.382)	(0.378)	(0.875)
Const.	-2.96	-3.56**	-7.31***	-3.64
Cluster bank-lever	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
N	521	521	177	177
Log likelihood	-283.71	-305.39	-87.32	-68.34
LR test	89.79***	67.11***	35.43***	21.33**
Pseudo R^2	0.14	0.10	0.17	0.14

The empirical model is defined in Table 3. The dependent variable is employed as the ratio of the volume of non-opaque securitization transactions to total assets in specifications (1a) and (2a) respectively. The dependent variable is included as the ratio of the volume of opaque securitization transactions to total assets in specifications (1b) and (2b) respectively. While non-opaque securitization transactions include Residential Mortgage Backed Securities (RMBS), Commercial Mortgage Backed Securities (CMBS), credit card receivables and consumer loans, opaque securitization transactions cover Collateralized Debt Obligations (CDO) and other securitizations.

Table 9
Sensitivity analyses: Regulatory and institutional environment

	Secvol (pre-crisis)			Secvol (crisis)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
OSP	0.044**			0.081*		
	(0.049)			(0.076)		
Capstring		0.171**			0.115*	
		(0.029)			(0.085)	
SMC			0.147*			0.087
			(0.091)			(0.674)
Liquidity $_{(t-1)}$	-0.002	-0.003	-0.002	-0.013**	-0.013**	-0.012**
	(0.365)	(0.327)	(0.409)	(0.019)	(0.012)	(0.016)
LL Reserves $_{(t-1)}$	-0.062**	-0.066**	-0.057*	0.090	0.113	0.074
	(0.046)	(0.034)	(0.057)	(0.236)	(0.164)	(0.311)
Tier1 $_{(t-1)}$	-0.020	-0.026	-0.029	0.018	0.013	0.012
	(0.473)	(0.404)	(0.315)	(0.732)	(0.814)	(0.829)
CIR $_{(t-1)}$	-0.010**	-0.011**	-0.010**	0.004	0.003	0.000
	(0.026)	(0.027)	(0.025)	(0.510)	(0.648)	(0.977)
Size $_{(t-1)}$	0.148***	0.170***	0.132***	0.364***	0.341***	0.332***
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
H-statistic	0.468***	0.398***	0.424***	-0.456	-0.366	-0.265
	(0.001)	(0.010)	(0.002)	(0.370)	(0.465)	(0.604)
Yield curve $_{(t-1)}$	0.317**	0.211	0.242**	0.349	0.322	0.289
	(0.015)	(0.116)	(0.035)	(0.132)	(0.162)	(0.219)
GDP	0.181*	0.192*	0.097	0.196	0.113	0.061
	(0.085)	(0.077)	(0.262)	(0.265)	(0.467)	(0.705)
Const.	-4.22**	-4.30**	-2.51*	-8.07**	-6.77**	-4.86*
Cluster bank-level	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	521	457	521	177	177	177
Log likelihood	-306.95	-261.11	-308.30	-100.82	-101.03	102.76
LR test	103.10***	90.03***	100.40***	40.44***	40.02***	36.56***
Pseudo R^2	0.14	0.14	0.14	0.17	0.17	0.15

The empirical model is defined in Table 3. Model specifications (1a) and (2a) include the official supervisory power (OSP), specifications (1b) and (2b) include regulatory capital stringency (Capstring) and specifications (1c) and (2c) include a country's stock market capitalization (SMC) to control for the regulatory and institutional environment.

Table 10
Correlation matrix

	Secvol	Sec	Liquidity $_{(t-1)}$	LL Reserves $_{(t-1)}$	Tier1 $_{(t-1)}$	CIR $_{(t-1)}$	Size $_{(t-1)}$	H-statistic	Yield curve $_{(t-1)}$	GDP
Secvol	1.00									
Sec	0.95***	1.00								
Liquidity $_{(t-1)}$	-0.05	-0.03	1.00							
LL Reserves $_{(t-1)}$	-0.09	-0.07	0.05	1.00						
Tier1 $_{(t-1)}$	-0.07	-0.06	0.25***	-0.18***	1.00					
CIR $_{(t-1)}$	-0.08	-0.06	0.22***	0.25***	-0.09	1.00				
Size $_{(t-1)}$	0.23***	0.25***	0.42***	0.01	0.02	0.19***	1.00			
H-statistic	0.05	0.05	-0.05	-0.12**	-0.01	0.16***	0.06*	1.00		
Yield curve $_{(t-1)}$	-0.08	-0.05	-0.06	0.20***	0.09	0.09	-0.05	0.12**	1.00	
GDP	-0.01	-0.01	0.27***	0.13**	-0.14***	0.09	0.15***	-0.20***	-0.07	1.00

***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Appendix B

Next to Tobit regressions, a random effects *logistic* regression model on panel data is used to analyze the impact of the explanatory variables on *the probability* that a bank engages in securitization activities.[18]

Following Cameron and Trivedi (2010) the logistic regression model is specified as

$$\Pr\left(y_{it} = 1 \middle| \mathbf{x}_{it}, \boldsymbol{\beta}, \alpha_i\right) = \Lambda\left(\alpha_i + \mathbf{x}'_{it}\boldsymbol{\beta}\right) \tag{B1}$$

where Λ is the logistic cumulative distribution function, α_i is for the individual effect for each bank i, and $\boldsymbol{\beta}$ is a vector of logistic regression coefficients. $\mathbf{x}_{it}$ is a vector containing the explanatory variables which may determine the bank's decision to securitize or not.[19] The binary response variable for bank i at time t is modeled as

$$y_{it} = \begin{cases} 1 & \text{if } y^*_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad \text{with} \qquad y^*_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + \alpha_i + \varepsilon_{it} \tag{B2}$$

indicating that the logistic model is motivated by a latent-variable model so that whenever a bank i performs at least one securitization transaction in year t, y_{it} exhibits the value of 1 and 0 if there is no securitization at all.

The following Table B1 presents results from the logistic baseline regressions. As shown, the Tobit model (Table 3, Appendix A) and the Logit model produce results of the same quality suggesting that the probability to securitize as well as the securitization amount are driven by the same determinants.

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18 Using a probit regression model as alternative estimation technique does not provide remarkably different results. We provide empirical results on request.

19 We employ the Gauss-Hermite quadrature method to approximate the maximum likelihood function of the estimators (see footnote 10).

Table B1
Logistic regression model (baseline regressions)

	Sec (full sample) (1)	Sec (pre-crisis) (2)	Sec (crisis) (3)
Liquidity $_{(t-1)}$	-0.020*	-0.011	-0.039**
	(0.059)	(0.552)	(0.034)
LL Reserves $_{(t-1)}$	-0.268*	-0.283*	0.094
	(0.053)	(0.095)	(0.727)
Tier1 $_{(t-1)}$	-0.033	-0.060	-0.023
	(0.740)	(0.735)	(0.910)
CIR $_{(t-1)}$	-0.026	-0.073***	-0.005
	(0.110)	(0.004)	(0.791)
Size $_{(t-1)}$	0.928***	1.042***	1.240***
	(0.000)	(0.001)	(0.003)
H-statistic	1.545**	2.719***	-1.076
	(0.029)	(0.003)	(0.551)
Yield curve $_{(t-1)}$	1.564**	1.880**	1.135
	(0.019)	(0.012)	(0.224)
GDP	0.368	0.503	0.232
	(0.351)	(0.358)	(0.644)
Const.	-15.74**	-16.95*	-16.99*
Cluster bank-level	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
N	698	521	177
Log likelihood	-347.27	-247.86	-84.11
LR test	115.94***	88.99***	35.41***
Pseudo R^2	0.14	0.15	0.17

The Logit panel model estimated is Sec $_{(i=bank,\ t=time)}$ = β_1 Liquidity$_{i,t-1}$ + β_2 LLReserves$_{,t-1}$ + β_3 TIER1$_{i,t-1}$ + β_4 CIR$_{i,t-1}$ + β_5 Size$_{i,t-1}$ + β_6 H-statistic$_{i,t}$ + β_7 Yield curve$_{i,t-1}$ + β_8 GDP$_{i,t}$ + α_i + $\varepsilon_{i,t}$. The dependent variable equals 1 if a bank issues a securitization transaction and 0 otherwise. Regression specification (1) refers to the entire sample period from 1997 to 2010, specification (2) includes the pre-crisis period (1997-2007) and specification (3) refers to the crisis period (2008-2010). p-values are in parenthesis. ***, **, *: statistically significant at the 1%, 5% and 10% level.

Estimation of the H-statistic

The H-statistic is estimated by the following reduced-form revenue equations (e.g., Claessens and Laeven, 2004) for domestic and foreign banks operating within each sample country's national border as the relevant market for the time period from 1997 until 2010:

$$ln(P_{it}) = \alpha + \beta_1 ln(W_{1,it}) + \beta_2 ln(W_{2,it}) + \beta_3 ln(W_{3,it}) + \gamma_1 ln(Y_{1,it}) + \gamma_2 ln(Y_{2,it}) + \gamma_3 ln(Y_{3,it}) + \delta D + \varepsilon_{it,} \quad \text{(B3)}$$

where P_{it} is the ratio of interest revenue to total assets (proxy for output price), $W_{1,it}$ is the ratio of interest expenses to total deposits and money market funding (to proxy for the input price of deposits), $W_{2,it}$ is the ratio of personnel expense to total assets (proxy for the price of labor), and $W_{3,it}$ is the ratio of other operating and administrative expenses to total assets (proxy for price of fixed capital), with i denoting bank i and t denoting year t. Additionally, we include the control variables $Y_{1,it}$ (ratio of equity to total assets), $Y_{2,it}$ (ratio of net loans to total assets) and $Y_{3,it}$ (log of total assets) to account for possible size effects. After estimating equation (A1) the H-statistic is calculated as $\beta_1 + \beta_2 + \beta_3$ for each country in our sample with H-statistic=1 indicating competitive banking markets, H-statistic between 0 and 1 suggesting monopolistic competitive markets and H-statistic<0 indicating monopolistic banking markets. As pointed out by Panzar and Rosse (1982, 1987) the estimated model parameters are only valid if the market is in equilibrium. Therefore, we control for this by estimating the following equation for each country in our sample:

$$ln(ROA_{it}) = \alpha + \beta_1 ln(W_{1,it}) + \beta_2 ln(W_{2,it}) + \beta_3 ln(W_{3,it}) + \gamma_1 ln(Y_{1,it}) + \gamma_2 ln(Y_{2,it}) + \gamma_3 ln(Y_{3,it}) + \delta D + \varepsilon_{it}, \qquad \text{(B4)}$$

where ROA is the pretax return on assets. To examine whether the market is in equilibrium we build the equilibrium statistic E (calculated as $\beta_1 + \beta_2 + \beta_3$) and test whether $E = 0$ applying an F-test (see also Molyneux et al. 1996). If the hypothesis is rejected the market is assumed to be not in a long-run equilibrium and in equilibrium otherwise.

Calculation of the Distance-to-Default (DtD)

In line with Merton (1973, 1974) the market value of a bank's equity capital can be modeled as a contingent claim on the residual value of its assets. Therefore, in case of a bank's default, the bank shareholders receive no compensation for their investment if the market value of bank assets falls below the market value of bank liabilities. In contrast, if the market value of banks assets exceeds the market value of liabilities bank shareholders obtain the difference between the market value of assets and liabilities. Consequently, the contingent claim on the residual value of bank assets can be modeled as a call option on the underlying bank using standard option-pricing models. Following the framework developed by Black and Scholes (1973), we assume the value of the call option of the market value of a bank's assets to follow a geometric Brownian motion:

$$dV_A = \mu V_A dt + \sigma_A V_A dz \tag{B5}$$

where dV_A is the change in the value of assets, V_A is the current value of assets, μ is the drift rate of assets, σ_A is standard deviation of assets and, dz equals a Wiener process.

More precisely, the market value of assets follows a stochastic process of the following form:

$$lnV_A^T = lnV_A + \left(\mu - \frac{1}{2}\sigma_A^2\right)T + \sigma_A \sqrt{T}\varepsilon \tag{B6}$$

where V_A^T indicates the asset value at time T (maturity of debt), μ is the drift parameter and ε is a random component (standard normal distributed) of a firm's return on assets. The distance from the default point (V_A=DB) can be expressed as follows:

$$D = lnV_A^T - ln\,DB = lnV_A + \left(\mu - \frac{1}{2}\sigma_A^2\right)T + \sigma_A \sqrt{T}\varepsilon - ln\,DB\,. \tag{B7}$$

DB represents the distress barrier defined as the face value of short term liabilities (maturity ≤ 1 year) plus half of the amount of long term liabilities (maturity > 1 year).

Rearranging equation (5), we attain

$$\frac{D}{\sigma_A\sqrt{T}} = \frac{ln\left(\frac{V_A}{DB}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}} + \varepsilon, \tag{B8}$$

and finally obtain the following definition of the *Distance-to-Default*:

$$DtD \equiv \frac{D}{\sigma_A\sqrt{T}} - \varepsilon = \frac{ln\left(\frac{V_A}{DB}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}. \tag{B9}$$

The *Distance-to-Default* is designed to indicate the number of standard deviations that the bank is away from the default point within a given time horizon (one year). The unobservable parameters V_A and σ_A can be calculated from the observable market value of equity capital (V_E) as well as the standard deviation of share price returns (σ_E) using Ito's lemma and the following system of equations:[20]

$$\begin{aligned} V_E &= V_A N(d_1) - DBe^{-rT} N(d_2), \\ \sigma_E &= N(d_1)\frac{V_A}{V_E}\sigma_A, \end{aligned} \tag{B10}$$

$$d_1 \equiv \frac{ln\left(\frac{V_A}{DB}\right) + \left(\mu + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}} = \frac{ln\left(V_A\, exp\left(\left(\mu + \frac{1}{2}\sigma_A^2\right)T\right)\right) - ln\, DB}{\sigma_A\sqrt{T}}, \tag{B11}$$

$$d_2 \equiv d_1 - \sigma_A\sqrt{T} = \frac{ln\left(\frac{V_A}{DB}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}} = \frac{ln\left(V_A\, exp\left(\left(\mu - \frac{1}{2}\sigma_A^2\right)T\right)\right) - ln\, DB}{\sigma_A\sqrt{T}}. \tag{B12}$$

Calculation of the z-score

We use a modified version of the z-score that builds upon the work by Altman (2000) and is calculated as follows:

$$z_{i,t} \equiv \frac{\mu_{i,t} + X_{i,t}}{\sigma_{i,t}} \tag{B13}$$

We calculate the z-score for each bank i in each single year t where μ is the return on average

[20] We retrieve the history of banks' stock prices from *Datastream Database* provided by *Thomson Financial Services*. The relevant estimates of the DtD are calculated using Matlab.

assets before taxes (ROAA), X is bank's equity capital in percent of total assets and σ equals the standard deviation of the ROAA. A lower z-score indicates a higher probability of insolvency risk and vice versa.