How to Measure Securitization: A Structural Equation Approach

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Abstract

Securitization is a popular concept in banking and finance. Empirical literature measures securitization with a wide range of variables, which raises the question how to measure securitization. Using a structural equation modeling approach, we examine whether proxy variables used in the literature have a common securitization factor. We find that there are two common factors for ABS-CDO securitization, and ABCP securitization. These factors correlate strongly with factors for loan sales and credit derivatives, indicating that these four factors together are used by banks to hedge credit risk. We present some recommendations to improve the measurement of securitization.

JEL classification: C38, C52, G21, G23, G32

Keywords: Securitization; Asset-Backed Securities; Collateralized Debt Obligations; Asset-Backed Commercial Papers; Loan Sales; Credit Derivatives; Credit Default Swaps; Latent Variables; Proxy Variables; Latent Variable Analysis; Structural Equation Modeling; Exploratory Factor Analysis; Confirmatory Factor Analysis

1. Introduction

With 884 hits on Web of Science and 2,441 hits on ScienceDirect[1], securitization is a popular concept in banking and finance. The reason for this academic popularity is due to the central role of securitization in the Global Financial Crisis (GFC; 2007-2008). Originally, securitization was designed to transfer risk from the balance sheets of banks to the market. Yet, due to flaws in its design, securitization led banks to reduce their loan screening and monitoring efforts, and offload low-quality assets to the market (cf. Agarwal et al. (2012), Beltran et al. (2017), Berndt and Gupta (2009), Dell'ariccia et al. (2012), Elul (2016), Jiang et al. (2014), Keys et al. (2010), Maddaloni and Peydró (2011), Mian and Sufi (2009), and Purnanandam (2011)). As a result, excessive risks built up in the financial system, eventually leading to the collapse of the world economy (Tooze, 2018)

Securitization refers to the sale of 'securities whose principal and interest payments are exclusively linked to a pool of legally segregated, specified, cash flows owned by a special purpose vehicle (SPV)' (Gorton and Metrick, 2013, p. 5). To measure securitization, empirical literature generally chooses one variable, most popular of which are securitized assets, securities issued, and credit exposure to securitization vehicles (see Table 1). What is more, the literature uses these variables to measure several forms of securitization. Most studies focus either on asset-backed security (ABS), collateralized-debt obligation (CDO), or asset-backed commercial paper (ABCP) securitization. As a result, we observe a proliferation of proxies used by the literature, which raises the question: how do we measure securitization?

The goal of this study is to analyze how to measure securitization with proxy variables. Essential to a good evaluation of securitization is its measurement. The results of this study can be used to improve how we measure securitization, which can in turn be used to answer

[1] As of August 2021. Subject areas: economics, and business finance (Web of Science); economics, econometrics, and finance, and business, management, and accounting (ScienceDirect)

a wide range of research questions. This study therefore does not focus on a specific research question used in the literature that analyzes the effects of securitization on some variable. To the best of our knowledge, we are the first to specifically focus on the measurement of securitization.

In this study we take a latent variable approach. Kmenta (1991) describes three main classes of latent variables. The first class includes variables for which exact measurements are unavailable, and which are characterized by measurement error. The second class involve unobserved variables that can be represented only through closely related proxy variables. And the third class consists of variables that are intrinsically not measurable, but are related to a number of measurable proxy variables. We believe securitization falls in the last class, because we cannot measure it, but we observe the usage many related proxy variables in the literature.

A popular way of dealing with latent variables like securitization is structural equation modeling (SEM). A typical structural equation model includes a regression-type part, which is usually a structural model, and a measurement part. The measurement part analyzes how to measure one or more latent variables with proxy variables. Or, vice versa, whether proxy variables have some common (latent) factor(s). A common factor is inherently unobservable, but is responsible for a part of the variation in each proxy variable. Accordingly, SEM uses the variation of multiple proxy variables to extract the common factor. Because securitization is unobservable, SEM allows us to study whether our proxy variables have a common securitization factor. Because securitization is part of banks' credit risk management, we also include loan sales and credit derivatives in the analysis. Loan sales refer to the sale of a (part of a) single loan or a pool of loans by writing a new claim that is linked to the loan or loan pool (Gorton and Metrick, 2013). Credit are financial contracts that allow firms to hedge credit credit risk without physically transferring assets off-balance-sheet. Loan sales and credit derivatives are both popular credit risk transferring techniques.

Our analysis uses data on U.S. commercial banks from the year-end Federal Reserve's Reports of Condition and Income (Call Reports), and the Home Mortgage Disclosure Act's Loan Application Register (HMDA LAR) between 2006 and 2018. These data sources are publicly available and include detailed information about securitization activities of commercial banks in the U.S.. The data includes number of proxy variables used in or based on the literature, as well as some new ones. The proxy variables measure three popular forms of securitization: asset-backed security (ABS) securitization, collateralized-debt obligation (CDO) securitization, and asset-backed commercial paper (ABCP) securitization. The resulting sample includes 980 unique banks with $1 billion or more in total assets, and 6,838 bank-years. In our sample, loan sales are much more popular than securitization. This is most likely because of government stimulus of the loan sales market, and because loan sales require less knowledge and money to perform, and is therefore more accessible for banks than securitization. By far the most popular securitization proxy variable are assets sold and securitized. Also, credit derivatives are popular instruments.

We analyze whether all proxy variables have a common factor using confirmatory factor analysis (CFA), which essentially is the measurement part of SEM. We find that the proxy variables for securitization have not one common factor, but two. These factors measure ABS-CDO securitization, and ABCP securitization, respectively. Next to two securitization factors, we also find separate factors for loan sales and credit derivatives. All four factors strongly correlate with each other, implying that securitization, loan sales and credit derivatives together are used by U.S. commercial banks to hedge credit risk. Banks that use one these techniques are more likely to use other as well. We furthermore find that ABS and ABS-CDO securitization have a correlation coefficient of over 0.81. These findings are consistent with the notion that ABCP securitization is used to fund ABS-CDO securitization.

In addition we find that credit default swaps are significantly related to ABS-CDO securization. Even though credit default swaps are credit derivatives, they most likely play an important role in ABS-CDO securitization as well. Credit default swaps are not related to ABCP securitization. Last, we find that a large part of the variation of the proxy variables is explained by our factor model.

Based on our results we present some recommendations how to improve the measurement of securitization. First, we recommend using multiple proxy variables to measure securitization, not one. Which proxy variables to include depends on which form of securitization needs to be measured, ABS-CDO or ABCP securitization. Even though these forms of securitization correlated strongly, they require different proxy variables. Second, studies on loan sales or credit derivatives again require different proxy variables. Still, if researchers are interested in synthetic securitization, we advise including credit default swaps as proxy variables. Third, because securitization, loan sales, and credit derivatives are closely related, we suggest placing securitization in the context of credit risk management. The close relatedness of these three techniques imply that findings on the effects of securitization might not be unique to securitization.

The remainder of the study is as follows. Section 2 discusses what securitization is, and what the most popular forms of securitization are. Section 3 briefly reviews a structural equation approach to latent variables. Next, section 4 presents the data, and discusses the proxy variables. Section 5 and 6 introduce and discuss the method and results, respectively. Section 7 concludes.

[Table 1 about here.]

2. Securitization

Securitization was pioneered by government-sponsored entities (GSEs) in the U.S. in the 1970s (Tooze, 2018, pp. 48–49).[2] Since the 1980s, private financial institutions also securitize. In this section we discuss securitization in more depth, and introduce the main forms of securitization. We include loan sales and credit derivatives in the discussion since they are an integral part of banks' risk management strategy together with securitization.

2.1. What is securitization?

Securitization is a process that transforms pools of loans into marketable securities. We can summarize this process in three steps (Deku and Kara, 2017). In the first step, a bank (or other financial institutions) transfers the rights to cash flows of financial assets or their underlying credit risk to a remote Special Purpose Vehicle (SPV). An SPV is an off-balance, unmanaged,[3] and bankruptcy-remote entity that is legally separate from its sponsor. An asset is viable for securitization if all underwriting decisions have been made, which means the financial institution only has to wait for cash flows to be repaid as promised. It does not matter who has originated the asset. Next, the SPV pools the assets and offers some form of credit enhancement. Credit enhancement allows asset pools to obtain investment-grade ratings from rating agencies, which makes them attractive to investors (Greenbaum and Thakor, 1987). In the last step, the SPV sells securities linked to the asset pools and distributes the cash flows of the asset pools to the investors until maturity.

Securitization can either be cash (true sale) or synthetic. Cash securitization involves the true sale of assets to an SPV in step one, which means that these assets are moved off the balance sheet of the securitizer. In contrast, synthetic securitization uses credit derivatives

[2] GSEs are quasi-governmental organizations established by U.S. Congress to create a secondary market for loans in the U.S.

[3] Unmanaged means that an SPV is *not* an operating entity.

to transfer the underlying risk of assets to an SPV. In this way, the securitizer retains the assets on its balance sheet. Credit derivatives 'are bilateral financial contracts with payoffs linked to a credit related event such as non-payment of interest, a credit downgrade, or a bankruptcy filing' (Minton et al., 2009, p. 2), and can also be used outside of securitization to hedge credit risk. The most well-known types of credit derivatives are Credit Default Swaps (CDSs), Total Return Swaps (TRSs), and Credit Options (COs).

The most common types of securities resulting from securitization are pass-through securities, asset-backed bonds, and pay-through securities (Deku and Kara, 2017; Greenbaum et al., 2019). In pass-through securities an SPV issues a single class of participation certificates to investors, where each certificate represents a claim against the entire loan portfolio. Asset-backed bonds are similar to pass-through contracts with one main difference: the securitizer sells the assets to a wholly owned subsidiary and not an SPV, which then securitizes the assets. As a result, the assets remain on the securitizers balance sheet. Last, pay-through securities offer an ordered structure of prioritized payments in the form of multi-class notes (also known as tranching). The tranching creates a distribution schedule often called a waterfall in which the first tranche has the first claim on the collateral cash flows, the second tranche the second claim, and so on (Fabozzi et al., 2006).

Loan sales are similar to the first step in securitization. But instead of selling assets to an SPV, banks sell their assets directly to investors on the market. Loan sales, therefore, do not transform the patterns of cash flows like securitization does. Securitizing banks often purchase loans via loan sales in order to diversify the collateral loan pools in their securitization activities.

2.2. Main forms of securitization

In practice, there are many different ways to securitize. We can group these different ways in several forms of securitization, most popular of which are asset-backed security (ABS) securitization, collateralized debt obligation (CDO) securitization, and asset-backed commercial paper (ABCP) securitization.[4] Figure 1 presents a schematic overview of these forms of securitization. The figure also includes loan sales and credit derivatives. We do not discuss these separately.

[Figure 1 about here.]

The quantitatively by far the most popular type is ABS securitization (light-gray area; (Gorton and Metrick, 2013)). ABSs are the product of a cash securitization process, and were first sold on the market in the 1970s. Originally ABSs had pass-through securities, but nowadays they have pay-through securities as well. Assets used as collateral vary from credit-card receivables, to mortgages, and small business administration loans. ABSs with (residential) mortgages as collateral are called (R)MBSs.

A second popular variety of securitization is CDO securitization (medium-gray area). CDOs are pay-through securities resulting from either a cash or synthetic securitization process, and were first sold on the market in the 1980s. The asset pools of CDOs are much more diversified that those of ABSs, and can include securities (often ABSs), credit derivatives or a mix of securities and assets (Fabozzi et al., 2006; Gorton and Metrick, 2013; Schönbucher, 2003).

A last popular type of securitization is Asset-Backed Commercial Paper (ABCP) securitization (dark-gray area). ABCP securitization is different from ABS and CDO securitization in that it involves asset transformation as well as maturity transformation: limited-purpose,

[4]We base the names of these forms of securitization on the names of the resulting securities.

managed vehicles such as ABCP-conduits or a Structured Investment Vehicles (SIVs) purchase high-quality medium- and long-term ABSs and fund themselves with cheap, highly rated, mostly short-term and medium-term commercial papers (Fabozzi et al., 2006; Gorton and Metrick, 2013). ABCP-conduits and SIVs are market-values vehicles, which requires them to get frequent portfolio ratings by rating agencies that determines how much the can leverage. The managed structure and the frequent portfolio ratings set these vehicles apart from ABS/CDO SPVs. This process can also be synthetic (not displayed in Figure 1). ABCP securitization often serves as funding for ABS securitization.

Our discussion shows that ABS, CDO, and ABCP securitization have a large overlap, but differ with respect to collateral assets, resulting securities, and the use of SPVs. Because of this, we believe these forms of securitization are not one and the same. In other words, we expect there are more than one common securitization factors. In addition, loan sales and credit derivatives are close related to securitization. Because of this, we obtain proxy variables for all five latent variables.

3. A Structural Equation Approach to Latent Variables

In this section we briefly discuss why SEM is a useful tool for dealing with latent variables. Throughout the section we use a simple structural model to illustrate the usefulness of SEM. The results of this simple model, however, are representative for more extensive setups. For a more generalized case, see Bollen (1989). We focus on the case when we only have one proxy variable to approximate one single latent variable. Because the proxy variable is only an approximation of the latent variable, there is some degree of measurement error in the model. Such measurement error leads to a biased estimation of the model's parameters.

Consider the following structural equation model:

$$y = \lambda\eta + \varepsilon, \tag{1}$$

$$x = \eta + u, \tag{2}$$

where y and x are observed variables, and ε and u are error terms. Assume that η is unobservable, and is approximated by x. Furthermore, assume x does not affect y, i.e. η is uncorrelated with ε, and u is uncorrelated with η and ε. Here equation (1) the regression-type part of SEM, and equation (2) is the measurement part. This structural equation model implies that x imperfectly measures the latent variable η, and therefore introduces some measurement error, u, into the model.

Suppose we ignore the latent variable in equation (1), and estimate the following model:

$$y = \lambda_x x + \varepsilon, . \tag{3}$$

We can use OLS to obtain an estimate for λ_x. Then, the OLS estimator for λ_x is (Bollen, 1989):

$$\lambda_x = \frac{cov(y,x)}{var(x)} = \lambda\frac{var(\eta)}{var(\eta) + var(u)}. \tag{4}$$

Clearly, using OLS provides us with a biased estimate for λ_x. This is because $\lambda_x < \lambda$, which means that the coefficient for an observed variable is attenuated with respect to the true coefficient for the latent variable. Only when $var(x) = var(\eta)$, i.e. $var(u) = 0$, the bias is zero. This situation occurs when we can perfectly approximate the latent variable with x, which implies that the latent variable is actually observable.

In all other situations we need a way to deal with attenuation bias, because $var(x) \neq$

$var(\eta)$. SEM offers a solution to these situations, but it requires the availability of multiple proxy variables. Without multiple proxy variables, we cannot identify $var(\eta)$, which would not allow us to obtain estimates for λ. Thus, SEM with multiple proxy variables allows us to obtain $\hat{\lambda}$. To do so efficiently, we need to know what the measurement model looks like. In our case, we need to know how to measure securitization.

4. Data

We obtain our data from two sources: the Federal Reserve's Reports of Condition and Income (Call Reports), and the Home Mortgage Disclosure Act's Loan Application Register (HMDA LAR). Both sources are publicly available and include detailed information on the securitization activities of U.S. financial institutions. Moreover, these data sources are widely used in the literature (see Table 1). The literature also uses various non-publicly available data sources. We believe these sources have a significant overlap with the Call Reports and the HMDA LAR, and do not necessarily provide more detailed information on securitization. The final sample runs from 2006 to 2018, and includes 980 unique banks, and 6,838 bank-years. We merge the two sources using the HMDA lender file (also known as 'the Avery file', cf. Bhutta et al. (2017)).

Call Reports The Call Reports require every national bank, state member bank, and insured non-member bank in the U.S to report quarterly. The Reports contain information on banks' balance sheets, income statements, and off-balance-sheet items. We only use the year-end filings, because some information on securitization is only filed once a year.

We confine our analysis to all FDIC-insured commercial banks with a physical location in the U.S.. Furthermore, we exclude all banks with total assets under $1 billion, because from 2017 onward only banks with more than $1 billion in total assets report information on ABCP securitization. Our sample starts in 2006, because the Call Reports include detailed information on credit derivatives from 2006 onward. Our sample ends in 2017, because from 2018 onward only banks with a total assets over $5 billion need to report on their ABCP securitization activities, which would severely reduce our sample size. Lastly, we fill missing values in RCFD variables with the corresponding RCON variables, we remove outliers in servicing fees, and fill the remaining missing values with zeros.

HMDA LAR The HMDA requires all eligible U.S. financial institutions to periodically and publicly disclose loan-level information about their residential mortgage lending activities. The data cover about 90% of all originated residential mortgages in the U.S. (Dell'ariccia et al., 2012). For each filed loan, the HMDA LAR includes information on whether the loan has been sold to a GSE, to a private party, or has been privately securitized.

The main limitation of the HMDA LAR is that it does not track loans through time, which means that we do not observe what happens to a loan outside of its year of origination. The HMDA LAR only tags loans as sold or securitized when they are sold or securitized in the year of origination. When a loan is sold or securitized in a different year of origination, it is tagged as not sold or securitized. The resulting measurement error might lead to an underestimation of the number of loans sold or securitized. Avery et al. (2007) argue that the bias is likely to be small, because many end-of-year applications are carried over into the following reporting year. As a result, most loan sales and securitization should be included in the HMDA LAR. We do not correct for this form of measurement error.

4.1. Securitization proxies

Table 2 presents an overview of all proxy variables used in this study. Most proxy variables are either used by or based on the literature. We also include a few proxy variables that have not been used by the literature.

For ABS securitization we have three unique proxy variables and three non-unique one. The three unique variables come from the Call Reports (loans sold and securitized with recourse), and from the HMDA LAR (residential mortgages sold and securitized). These variables capture the assets sold that serve as collateral for (R)MBSs and ABSs. Since we lack the detail, these variables can also partly capture CDO securitization. However, since CDOs often have ABSs as collateral, the share of CDOs in these three proxy variables is likely to be small. The first non-unique proxy variable measures securitization income. This variable most likely also captures income from CDO/ABCP securitization. The other two non-unique proxy variables measure small business obligations (SBOs) sales, and servicing fees. SBO sales may or may not be securitized, meaning that it might measure loan sales and CDO securitization. Servicing fees are income from servicing mortgages, credit cards, and other financial assets held by others, and might include income from servicing loans sold or securitized by others. This variable also measures loan sales and CDO/ABCP securitization.

We have three unique proxy variables for CDO securitization. These variables capture the amount of credit default swaps (CDSs), total return swaps (TRSs), and credit options (COs) purchased by the bank. As a result, these variables only measure synthetic CDOs. These proxy variables might not be perfect, however. Since credit derivatives are also used in isolation from securitization to hedge credit risk, the variables might not only capture securitization. The proxy variables might therefore not specific enough.

We include four unique proxy variables for ABCP securitization. All four proxy variables come from the Call Reports. Two measure the amount of credit exposure to ABCP conduits (owned by the bank itself, or by others). The other two quantify the amount of unused commitments to ABCP conduits.

Last, we include five unique proxy variables for loan sales. Two come from the Call Reports and capture loans sold with recourse and not securitized, and two come from the

HMDA LAR and measure residential loans sold to GSEs and private parties, respectively.[5] The HMDA loan sales include loans with and without recourse. The fifth variable quantifies the income from loan sales.

There are more proxy variables available in the Call Reports. Because of issues with data quality, we do not include these variables to the analysis. For example, the Call Reports also include information on credit exposure and unused commitments to securitization facilities sponsored by others. Between 2009 and 2010 we observe a structural break in these variables. Because of this, we do not include these variables in our data. In addition, the Call Reports includes information on the assets and liabilities of SPV and ABCP conduits from 2011 onward. These variables, however, generally have low variation. The Call Reports do not include information on the issuance of securities resulting from securitization (ABSs, CDOs, or ABCPs).

[Table 2 about here.]

4.2. Summary statistics

Tables 3 and 4 present the summary statistics and the number of securitizers per proxy per year, respectively. We observe that loan sales are much more popular than securitization. For all loan sales proxy variables we observe more banks reporting information than for all other proxy variables, except net servicing fees. The popularity of loan sales is most likely driven by the fact that GSEs stimulate the sale of eligible loans. Loan sales are also much less knowledge-intensive than securitization. SBOs are only sold in very low quantities.

Among the securitization proxy variables, ABS securitization in the form of assets sold and securitized are most popular. Second most popular are CDSs and TRSs purchased. CDSs are used in by far the largest amounts, and have the greatest variation. ABCP securitization

[5] Recourse forces banks to retain at least part of the risk of loan sold or securitized, either by implicit guarantee or by retaining a fraction of the assets on-balance sheet.

is only performed by a small group of banks. The banks that perform ABCP securitization do so in large amounts. We drop the variable for credit exposure to ABCP (others) from our analysis due to low variation and too few observations.

[Table 3 about here.]

[Table 4 about here.]

Figure 5 contains the sample correlation matrix of the data. This correlation matrix serves as input for our factor model. We do not discuss the figure in detail.

4.3. Exploratory factor analysis

In order to get a better understanding of the underlying latent structure of our proxy variables, we perform an exploratory factor analysis. The goal of the analysis is to determine the appropriate number of common factors, and to show which variables are suitable indicators of the latent variables. We use the information from this analysis as input for our model specification, and follow the procedure described by Brown (2015, p. 34). We use the principle factors algorithm implemented by FactorAnalyzer in Python, which is more robust to deviations from normal than maximum likelihood. The algorithm does not provide goodness-of-fit indices. Because of the absence of goodness-of-fit indices we use this analysis as a guideline only. We standardize the data.

[Table 5 about here.]

First, we determine the appropriate number of factors. We use two complementary approaches: Horn's parallel analysis and rule of thumb eigenvalue > 1. In Horn's parallel analysis we generate eigenvalues from monty-carlo simulated matrices with the same size as the data, and compare the average of the generated eigenvalues with the eigenvalues generated from the data. The appropriate number of factors, then, equals the number of eigenvalues generated from the data are greater than the monte-carlo generated eigenvalues. We plot both approaches in Figure 4. The appropriate number of factors are four and five based on the parallel analysis and eigenvalue rule of thumb, respectively.

Table 5 displays the results of the four and five factor model using the promax rotation.[6] We consider a factor loading to be salient, or meaningfully related to a factor if it is greater than 0.4.[7] The factor loadings of the four and five factor model are very similar. Proxy variables for ABS/CDO/ABCP are salient in first factor in the four factor model. In the second factor, only proxy variables for loan sales are salient. We can therefore label these factors as 'securitization' and 'loan sales', respectively. Factors three and four only have two salient factor loadings each, which means that they are poorly defined. There are a few proxy variables that have no salient loadings, namely: other assets sold, and not securitized; securitized (HMDA); and Securitization income.

The five factor model yields similar results. We can provide the same interpretation for the first two factors as in the four factor model. The rest of the factors are poorly defined. We also find the same poorly defined proxy variables, except securitization income.

The exploratory factor analysis shows a couple of things. First, the appropriate number of common factors is four or five. Second, proxy variables for ABS/CDO/ABCP securitization group together well, as do the variables for loan sales. Third, net servicing fees likely captures something else than securitization or loan sales. The same holds for SBOs sold. For this reason, we drop these variables from the list of proxy variables.

[6] Factor rotation helps with the interpretability of the factors. The promax rotation is an oblique rotation that allows the factors to inter-correlate, which leads to a more realistic representation (Brown, 2015).

[7] Some studies also use 0.3 as a cutoff (Brown, 2015). For this reason, we highlighted the loadings between 0.3 and 0.4 as well.

5. Model specification

5.1. Confirmatory factor analysis

To study the relationships between our proxy variables and their latent factors we use a confirmatory factor analysis (CFA) framework. Essentially, CFA is identical to the measurement part of SEM. We use CFA to test whether our proxy variables share a common cause, i.e. whether they are influenced by a common factor (Brown, 2015; Hoyle, 2012). In this case, we test whether the securitization proxy variables are one or multiple common securitization factors. The main benefit of CFA is that it allows us to test some hypothesized theoretical model.

The goal of CFA is to estimate a common factor model in which the number of factors, the pattern of the factor loadings, the cross-loadings, etc. are pre-specified based on some theory. The common factor model is as follows (Brown, 2015):

$$y = \Lambda_y \eta + \varepsilon. \tag{5}$$

And in expanded matrix form:

$$\Sigma = \Lambda_y \Psi \Lambda_y' + \Theta\varepsilon, \tag{6}$$

where y is a row vector with dimension p of observed (manifest) variables, η is a row vector with dimension m of latent factors, Λ_y is a $p \times m$ matrix of factor loadings, and ε is a row vector with dimension p of unique variances. Furthermore, Σ is a $p \times p$ symmetric correlation matrix of the observed variables, Ψ is a $m \times m$ symmetric correlation matrix of the latent factors, and $\Theta\varepsilon$ is a $p \times p$ matrix of unique variances, where the off-diagonal are error covariances.

Equation (6) shows that the variance of an observed variable can be decomposed in a variance that comes from some latent factor and a unique variance. CFA then aims to find a set of parameters (factor loadings/variances and error variances/covariances) such that the model-implied variance-covariance matrix, Σ, resembles the sample variance-covariance matrix, S, as closely as possible. When we know Σ, we can calculate the common factors, η, and use these in the regression-type part of SEM.

We use a robust maximum likelihood procedure (MLR) implemented by Lavaan in R to estimate the parameter matrix, Λ_y. The MLR procedure combines the fit function of maximum likelihood with robust (Hubert-White) standard errors and scaled test statistics (equivalent to the Yuan-Bentler test statistic) to account for non-normality in the data. Generally, this procedure produces reliable estimates and standard errors under slight to moderate deviations from normality. The maximum likelihood fit function is as follows:

$$F_{ML} = ln|S| - ln|\Sigma| + trace[(S)(\Sigma^{-1})] - p, \tag{7}$$

where $|\cdot|$ is the determinant of a matrix, p are the number of input indicators, and ln is the natural logarithm.

Furthermore, we log transform the data as follows: $ln(x + 1 - \min(x))$. Where x is an observed variable and $\min(\cdot)$ is the minimum of x. We subtract the minimum of x to prevent any negative values. In practice, we only have negative values for the variables loan sales income, and securitization income. In all other cases the minimum of x is zero.

5.1.1. Hypothesized model and model estimation

Figure 2 displays the path diagram of the hypothesized model we test with our CFA framework. The model is based on our discussion in section 2. A latent factor (ξ) is represented by a circle, observed variables (X) are in a box and unique variances (δ) have no frame. Arrows from a latent factor to an observed variable represent the factor loadings, λ. To prevent clutter, the figure does not display the lambdas explicitly. Variances and covariances between factors are represented by $\phi_{\cdot,\cdot}$, and shared variances between observed variables by $\delta_{\cdot,\cdot}$. The latter can occur when part of the shared variance of two variables is due to an outside cause, and not the common factor.

[Figure 2 about here.]

The model includes five latent factors, four of which measure securitization and one loan sales. We don't include a separate factor for credit derivates, since our explanatory factor analysis showed these variables group well with a number of securitization variables. The model includes a second-order structure for securitization. This means that a portion of the variance of the ABS/CDO/ABCP securitization factors come from a common securitization factor. Furthermore we allow for covariance between the higher-order securitization and loan sales. The model also includes several shared variances. First, we add shared variances among all HMDA variables to account for a possible difference in measurement scale relative to the Call Report variables. Second, we add shared variances between residential loan sales (Call Reports) on one side and the two HMDA loan sales variables, because they overlap in their measurement of which loans are sold. Similarly, we add a shared variance between residential assets sold and securitized (Call Reports), and HMDA securitized assets. Third, we add a shared variance between unused commitments and credit exposure to own ABCP conduits. Both variables most likely measure the connection to the same ABCP conduits.

The estimation procedure is as follows (cf. Brown, 2015). First, we estimate the hypothesized model without the second-order structure. Instead we allow the two securitization, loan sales, and credit derivative factors to correlate. Second, we assess the fit of the model (see section 5.2). If the fit is poor, we re-specify (see section 5.3) and re-estimate the model without a second-order structure. Last, we estimate the (re-specified) model with second-order structure if the fit of the first-order model is good.

5.2. Goodness of Fit

We use a number of fit indices to assess the fit of the estimated factor model see Table 6. When the fit of the model is good, Σ closely resembles S. We use a Yuan-Bentler equivalent χ^2. This statistic is robust against deviation from normality. For a good fit, the p-value needs to be over 0.05 ($H_0 : \Sigma = S$). The χ^2 test statistic is inflated by the sample size, and is therefore not reliable on its own. We therefore include a number of other statistics as well. First, we use the Standardized Root Mean Square Residual (SRMR) to asses the absolute fit of the model. De SRMR evaluates the differences between S and Σ. The statistic varies between 0 and 1, where 0 indicates a perfect fit. For a good fit, the SRMR is < 0.08. Second, we use the Root Mean Square Error of Approximation (RMSEA). The RMSEA corrects for the parsimony of the model, and prefers models with fewer freely estimated parameters over models with more. The RMSEA needs to be close or below 0.06. We include a second parsimony fit index, the Relative Non-centrality Index (RNI), which should be > 0.95. The third set of fit indices consider the comparative fit of the model. They evaluate whether the user-specified model is better than some baseline model, which only estimates variances. We consider the Tucker–Lewis Index (TLI), the Comparative Fit index (CFI), the Normed Fit Index (NFI), and the Incremental Fit Index (IFI). The fit is good when the indices are > 0.95. The TLI and the CFI are acceptable between 0.9 and 0.95. Last, we report the Akaike and Bayesian Information Criteria (AIC and BIC, respectively) for model comparison.

We also report the Goodness-of-Fit Index (GFI) and the Adjusted Goodness-of-Fit Index (AGFI). These indices, however, are very sensitive to sample size, and are therefore not very reliable (Hoyle, 2012). For the sake of completeness, we include these indices.

The fit of the model is good when the SRMR is < 0.08, RMSEA is close or below 0.06, and the TLI or the CFI is > 0.95 (cf. Brown, 2015; Hu and Bentler, 1999). In this way we make sure the absolute, parsimony fit, and comparative fit of the model is correct. If one of these fit indices is not good, it points to flaws in the model.

[Table 6 about here.]

5.3. Model respecification

If the fit of the model is poor, we need to respecify the model. We use standard residuals and modification indices to identify areas of misfit of the model. Any changes we make based on these two statistics needs to be based on theory, otherwise the model might overfit, or might be nonsensical.

Standardized residual provide specific information about how well the variances and covariances are reproduced by the model. We can calculate standardized residuals by dividing the residual covariances by their sample standard deviations, $(s_{ij} - \hat{\sigma}_{ij})/\sqrt{s_{ii}}\sqrt{s_{jj}}$, where s, and σ are elements of S and Σ, respectively. Standardization means we can interpret the residuals as z-scores. Therefore, each standardized residual over 2.58 (or under -2.58) can be seen as significantly different from zero. Positive standardized residuals show that the model underestimates the relationship between two indicators, which indicates the need of extra parameters. Conversely, negative standardized residuals show an overestimation of the relationship between two indicators.

Modification indices, also known as Lagrange multipliers, calculate the expected change in χ^2 by releasing a fixed parameter. In other words, a modification index is roughly the difference between two models, where one model has one more freely estimated parameter. A large, positive modification index indicates a large expected improvement in χ^2. In addition to the modification indices, we also present the expected parameter change (EPC) index. These indices show the change in parameter estimate of the freed parameter. A large EPC indicates a large expected value change in the parameter estimate.

6. Results

6.1. Hypothesized model

Table 7 presents the fit indices of the hypothesized model *without* second-order securitization. For the parameter estimates, modification indices, and standardized residuals, see appendix B.2.

[Table 7 about here.]

The fit of the model is acceptable, but can be improved. The SRMR is good with 0.0341. The TLI and CFI are acceptable with 0.9114 and 0.9367, respectively. And the RMSEA is poor with 0.0655. All of the other fit indices indicate a poor fit of the model, which means the model does not fit the data well. We therefore need to respecify the model. For this reason, we do not discuss the parameter estimates. To respecify the model, we check the standardized residuals and modification indices.

The standardized residuals show that the model underestimates the relationships between residential assets sold and securitized (Call Reports) and loan sales to GSEs and private parties (HMDA). All these variables involve residential assets, but do not include the same assets. Adding extra parameters, therefore, seems not necessary from a theoretic point of view. Also, relationships between CDSs and various other variables are underestimated, which implies that CDSs should be included in other securitization factors as well. Relationships between the other types of credit derivatives and other variables, however, are often overestimated, which indicates that the removal of the other credit derivatives from the model might be in order.

The modification indices show that the model fit probably improves by adding credit derivatives, and especially CDSs, to the factors for loan sales, and ABS and ABCP securitization. Moreover, the model fit might benefit from adding shared variances among the credit derivatives. The remaining modification indices are theoretically not logical.

Based on the standardized residuals and modification indices we can respecify our hypothesized model (see Figure 3). Proxy variables for credit derivatives, and especially TRSs and COs are not specific enough to capture synthetic CDO securitization well. CDSs on the other hand, are likely to improve the fit of the model when added to ABS and ABCP securitization. Because of this we add CDS to ABS and ABCP securitization. Next, we rename ABS securitization to ABS-CDO securitization, and replace CDO securitization with a factor capturing credit derivatives, which is measured by CDS, TRS and CO. ABS-CDO securitization now captures ABS, and cash and synthetic CDO securitization. We do not remove any variables from the model. We first estimate the model without a second-order structure.

[Figure 3 about here.]

6.2. Respecified model

The overall fit of the respecified first-order model is good (see Table 8, column one). We obtain good values for SRMR (0.0298), RMSEA (0.0552), CFI (0.9549), RNI (0.9549), and GFI (0.9630). The value of TLI is acceptable at 0.9370. In addition, the AIC and BIC are better than the hypothesized first-order model, which is good. The few remaining fit indices indicate a poor fit. Based on the SRMR, RMSEA and CFI, we believe that the fit of the model is good. Next, we estimate the respecified second-order model.

[Table 8 about here.]

The second column of Table 8 displays the fit indices of the respecified second-order model. The overall fit of the model is acceptable, but worse than the respecified first-order model.

The SRMR and RMSEA are good at 0.0375 and 0.627, respectively. The GFI is also good at 0.9554. The TLI and CFI are acceptable at 0.9173 and 0.9410, respectively. The remaining indices signal that the model has a poor fit. Based on the SRMR, RMSEA and CFI/TLI, we believe that a second-order structure is not appropriate for the data. In other words, these results imply that ABS-CDO and ABCP securitization are not driven by a higher-order securitization factor. The respecified first-order model shows that two common factors for securitization, and one factor for loan sales and credit derivatives, respectively, are most appropriate. We continue with discussing the parameter estimates, modification indices and standardized residuals of the respecified *first-order* model. For the parameter estimates, modification indices and standardized residuals of the respecified second-order model, see appendix B.4.

Table 9 introduces the parameter estimates, and (completely) standardized parameters of the respecified first-order model. We find that each factor correlates strongly and significantly with each other individual factor (see the completely standardized parameters for factor covariances $\phi_{\cdot,\cdot}$). We especially find strong correlations between ABS-CDO securitization and ABCP securitization (0.8001), loan sales and ABS-CDO securitization (0.9157), credit derivatives and ABCP securitization (0.8115). The remaining factor correlations are a little less strong, with 0.40118 (loan sales and credit derivatives), 0.5993 (loan sales and ABCP securitization), and 0.6577 (ABS-CDO securitization and credit derivatives). These strong correlations indicate that securitization, loan sales, and credit derivatives are complementary credit risk management tools. Banks that use one of these tools are more likely to use one of the other tools as well. Especially, securitizing banks are likely to be involved in both ABS-CDO and ABCP securitization, suggesting that ABCP securitization is used to fund ABS-CDO securitization.

[Table 9 about here.]

In general we find significant factor loadings (parameter estimates for $\lambda_{\cdot,\cdot}$). We find that all proxy variables for loan sales except income from loan sales ($\lambda_{LS,5}$) are significantly related to the factor loan sales. Income from loan sales is therefore likely not to capture the full scope of securitization. On the other hand, income from loan sales is the only variable in the factor that is a flow variable. The rest are stock variables, which could explain its insignificance. Next, we find that all proxy variables for ABS-CDO securitization have significant loadings. Some of these variables have high completely standardized loadings. For example, the completely standardized factor loadings for residential assets sold and securitized on ABS-CDO is 0.6644, meaning that for every increase of one unit in ABS-CDO, residential assets sold and securitized increase by 0.6644. Also for all proxy variables for credit derivatives are siginificant, with high completely standardized loadings. Last, we find that unused commitments and credit exposure to ABCP conduits are significantly related to ABCP securitization. Income from securitization ($\lambda_{ABSCDO,10}$), and CDSs ($\lambda_{ABSCDO,12}$) are not related to ACBP securitization, which implies that income from securitization is driven by ABS-CDO securitization and not ABCP securitization, and that CDSs do not capture synthetic ABCP securitization well. CDSs might be used synthetic ABCP securitization, but probably only in small amounts.

We can also use the completely standardized factor loadings to calculate the communalities, or the proportion of variance of an observed variable explained by the factor or factors (one minus the residual variance, $\delta_{\cdot,\cdot}$). Table 10 displays the communalities of all observed variables. We observe that a high percentage of variation in other assets sold and not securitized, residential and other assets sold and securitized, and all credit derivatives and ABCP-variables are explained by the factors. These results imply that these variables are largely driven by some latent processes. The remaining observerd variables have low to near-zero communalities, which means that the factors hardly explain any of their variance.

[Table 10 about here.]

Last we check the parameter estimates of the unique and shared variances in the model. We find that the variance of income from loan sales and income from securitization are completely explained by their respective factors, because their unique variances ($\delta_{5,5}$ and $\delta_{10,10}$) are not significantly different from zero. Moreover, we find the shared variances among the HMDA variables are significant, indicating that these variables have a different measurement scale than the Call Reports variables. Also the shared variances between residential loans sold and (not) securitized (Call Reports) and the respective HMDA counterpart are significant. This is also the case for the shared variance between unused commitments and credit exposure to own ABCP conduits.

7. Conclusions

Securitization is a popular topic in banking and finance. Empirical literature on securitization uses a wide range of variables to measure it, raising the question how to measure securitization. In this study we analyzed how to measure securitization with proxy variables. Using a structural equation modeling approach, we examined whether securitization proxy variables share a common factor. Using data on U.S. commercial banks between 2006–2018, we found that there is not one but two common factors. These two factors measure ABS-CDO securitization and ABCP securitization, respectively. Next to these two factors, we found two separate factors for loan sales and credit derivatives. All four factors are strongly related to each other, suggesting that they together are used by U.S. commercial banks to hedge credit risk. In fact, if banks use one of the four factors, they are more likely to use the other as well. Our findings are also consistent with the fact that ABCP securitization is used as funding for ABS-CDO securitization. Moreover, we found that credit default swaps play an important role in synthetic securitization. Last, our factor model explains a large part of the variation in our proxy variables.

We present some recommendations based on our results. First, we suggest using not one but multiple proxy variables to measure securitization. Using multiple proxy variables allow researchers to optimally use the available information, and to isolate the latent factor. Which proxy variables to include depends on which form of securitization is studied. Even though we found a strong correlation between the securitization factors, they require different proxy variables. Second, researchers interested in loan sales or credit derivatives should again use a different set of proxy variables. If researchers are interesting in synthetic securitization, however, we recommend using credit default swaps as a proxy variable as well. Third, securitization, loan sales, and credit derivatives should be seen as part of banks' credit risk management. All three techniques correlate strongly with each other. In addition our factor model explains a large part of the variance in the proxy variables, suggesting that findings on the effects of securitization might not be unique to securitization. In fact, loan sales and credit derivatives might have similar effects. When this is the case, we recommend that researchers place the results in the broader context of credit risk management.

In this study we took a SEM approach. An alternative approach is that of Lubotsky and Wittenberg (2006), who consider a situation in which a latent variable is a right-hand-side variable in a regression, and is measured by multiple proxy variables. The authors then show that attenuation bias caused by measurement error is *minimized* when all proxy variables are added to a regression simultaneously. The net effect of the proxy variables, then, is calculated by taking the sum of all coefficients. This approach is easy to implement, requires few assumptions, and reduces attenuation bias substantially, but it does not remove attenuation bias altogether. Like SEM, this approach requires the availability of multiple proxy variables. Our results are also useful in determining which proxy variables to include in this approach.

Securitization in the U.S. is performed by a small number of very large banks. Our sample most probably includes all securitizing banks. But, by limiting the sample to banks with total assets in excess of $1 billion, we exclude many banks that might use loan sales and credit derivatives. We therefore expect that our results are sensitive to the sample. Most securitizing banks are likely to also use loan sales and securitization. Non-securitizing banks, however, aren't very likely to ever securitize. We believe that the correlation between loan sales and credit derivatives for this group of banks is positive, but the correlation between securitization and either loan sales or credit derivatives is zero.

A limitation of this study is that the data lacks detail. On the one hand, we do not have any proxy variables that measure the issuance of securities resulting from securitization. On the other hand, the data misses specific information on CDO securitization, and synthetic securitization. Including such information should improve our study.

A. Exploratory Factor Analysis Scree Plot

See Figure 4.

[Figure 4 about here.]

B. Extra Tables and Figures Confirmatory Factor Analysis

B.1. Input Correlation Matrix

See Figure 5.

[Figure 5 about here.]

B.2. Parameter Estimates, Modification Indices, and Standardized Residuals First-Order Model

For the parameter estimates and the modification indices of the non-nested model, see Tables 11 and 12, respectively. For the standardized residuals, see Figure 6.

[Table 11 about here.]

[Table 12 about here.]

[Figure 6 about here.]

B.3. Modification Indices, and Standardized Residuals Respecified First-Order Model

[Table 13 about here.]

[Figure 7 about here.]

B.4. Parameter Estimates, Modification Indices, and Standardized Residuals Respecified Second-Order Model

For the parameter estimates and the modification indices of the non-nested model, see Tables 14 and 15, respectively. For the standardized residuals, see Figure 8.

[Table 14 about here.]

[Table 15 about here.]

[Figure 8 about here.]

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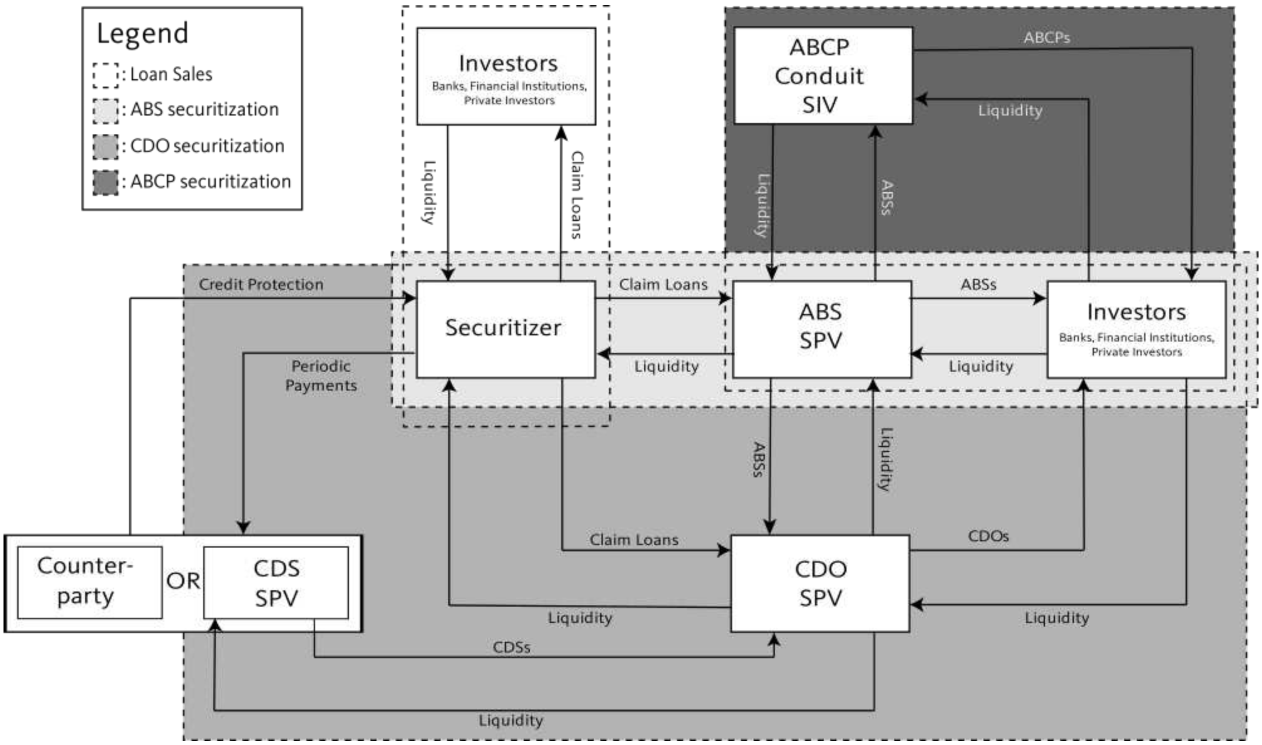
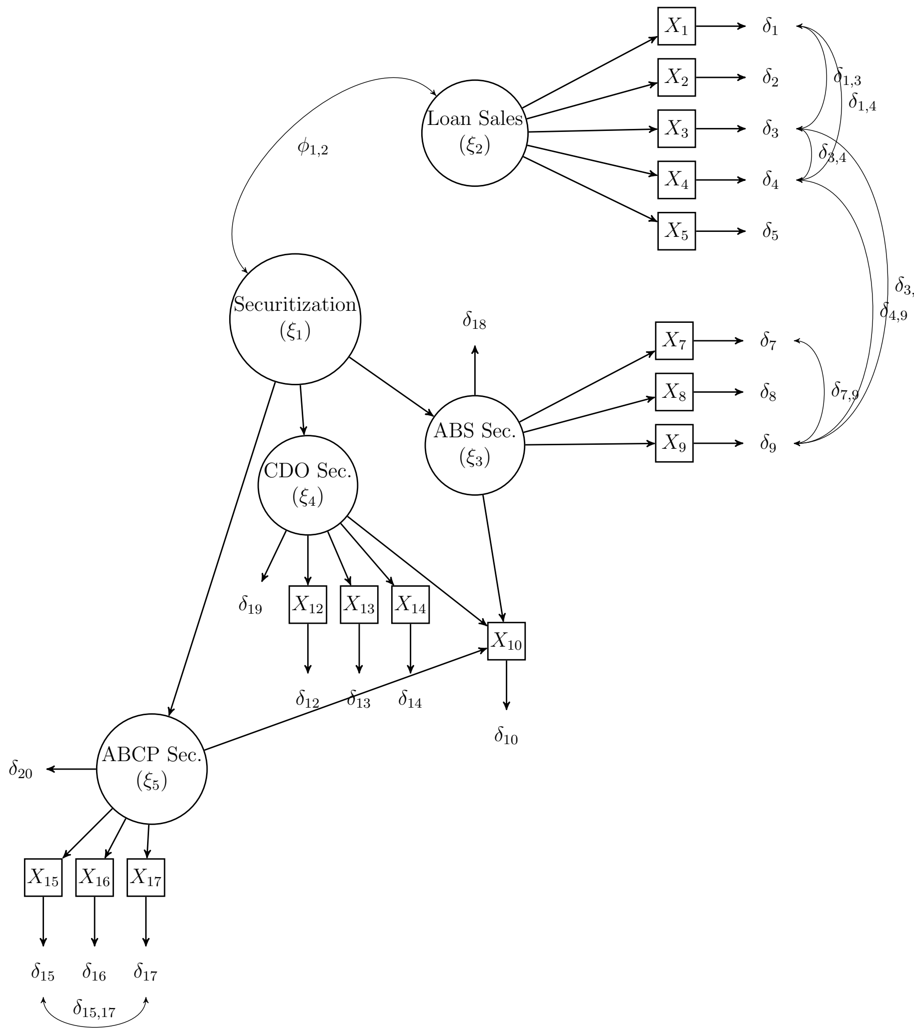
Figure 1: Common Varieties of Securitization



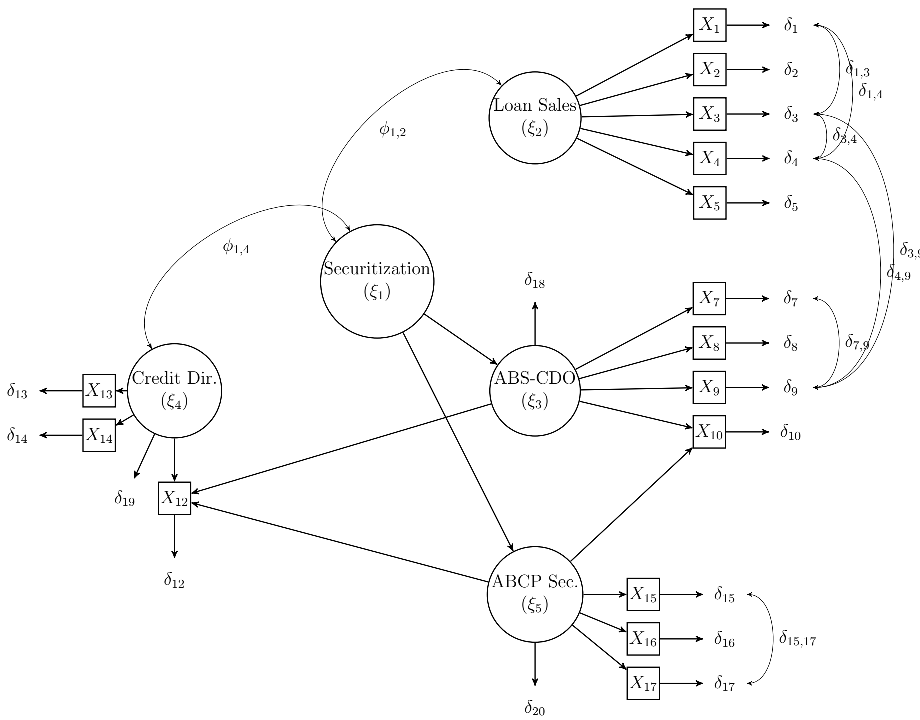
Notes. ABS securitization is the process in which loans are sold by banks to Special Purpose Vehicles (SPVs) for liquidity. SPVs pool the loans and sell securities to investors. CDO SPVs bundle ABSs or CDSs in a similar fashion and sell tranched Collateral Debt Obligations (CDOs). Asset-Backed Commercial Papers (ABCPs) are short-term or medium-term commercial papers that are used to fund purchases in ABSs. These papers are issued by ABCP conduits or Structured Investment Vehicles. The figure also includes loan sales and credit derivatives. Loans sales are the loans sold by banks to investors for liquidity without securitization. Credit derivatives are purchased by the securitizer from some counterparty, and not from a CDS SPV.

Figure 2: Path Diagram of the Hypothesized Factor Model



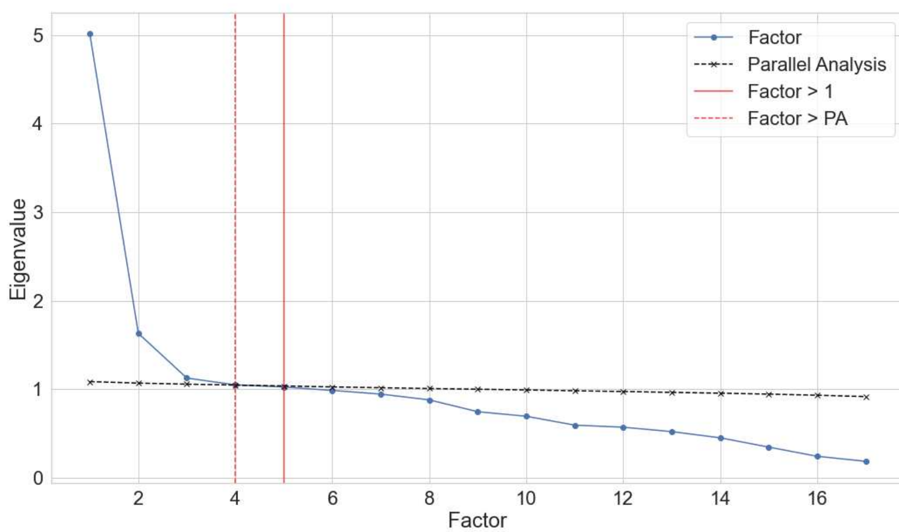
Notes. The figure displays the hypothesized factor model of securitization and loan sales. A latent factor (ξ) is presented in a circle, observed variables (X) are in a box, and error terms (δ) have no frame. Variances and covariances between factors are represented by $\phi_{\cdot,\cdot}$, and shared variances between observed variables by $\delta_{\cdot,\cdot}$. In the figure, each arrow from a latent to an observed variable represents the factor loadings λ. The model includes a second-order structure for securitization, and allows for some covariance between the higher-order securitization and loan sales.

Figure 3: Path Diagram of the Respecified Factor Model



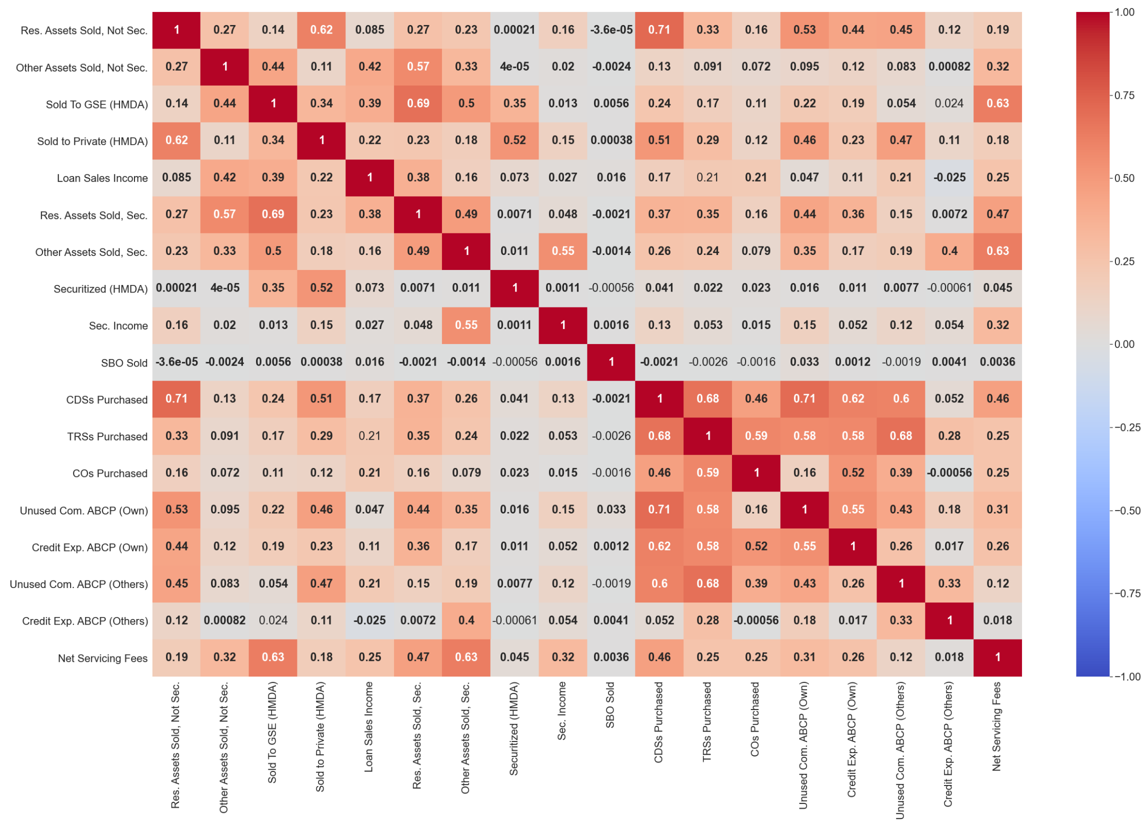
Notes. The figure displays the respecified factor model of securitization and loan sales. A latent factor (ξ) is presented in a circle, observed variables (X) are in a box, and error terms (δ) have no frame. Variances and covariances between factors are represented by $\phi_{\cdot,\cdot}$, and shared variances between observed variables by $\delta_{\cdot,\cdot}$. In the figure, each arrow from a latent to an observed variable represents the factor loadings λ.

Figure 4: Scree Plot and Parallel Analysis



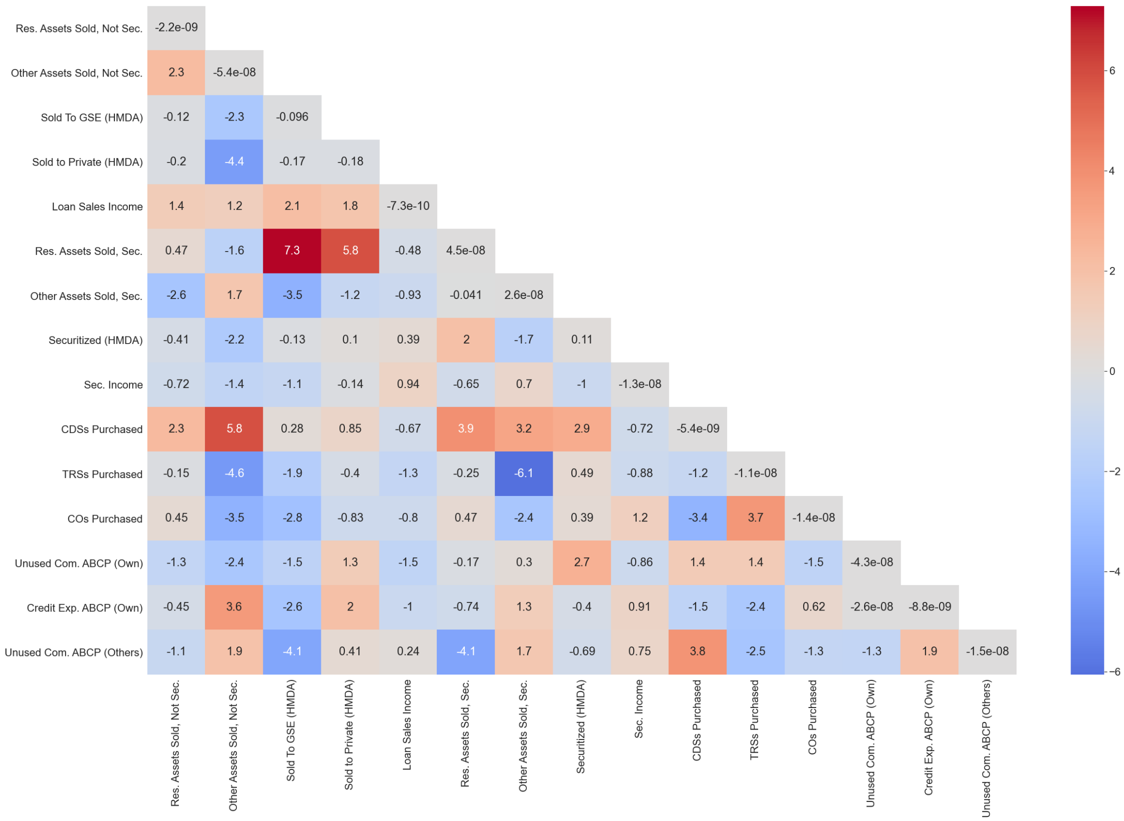
Notes. The figure plots of the eigenvalues of the factor correlation matrix (solid blue line) and a parallel analysis (dashed black line) to determine the optimal number of factors to include in the explanatory factor analysis. The solid red vertical line indicates the number of eigenvalues greater than one, and the dashed red vertical line where the number of eigenvalues greater than the respective eigenvalue of the parallel analysis.

Figure 5: Input Correlation Matrix



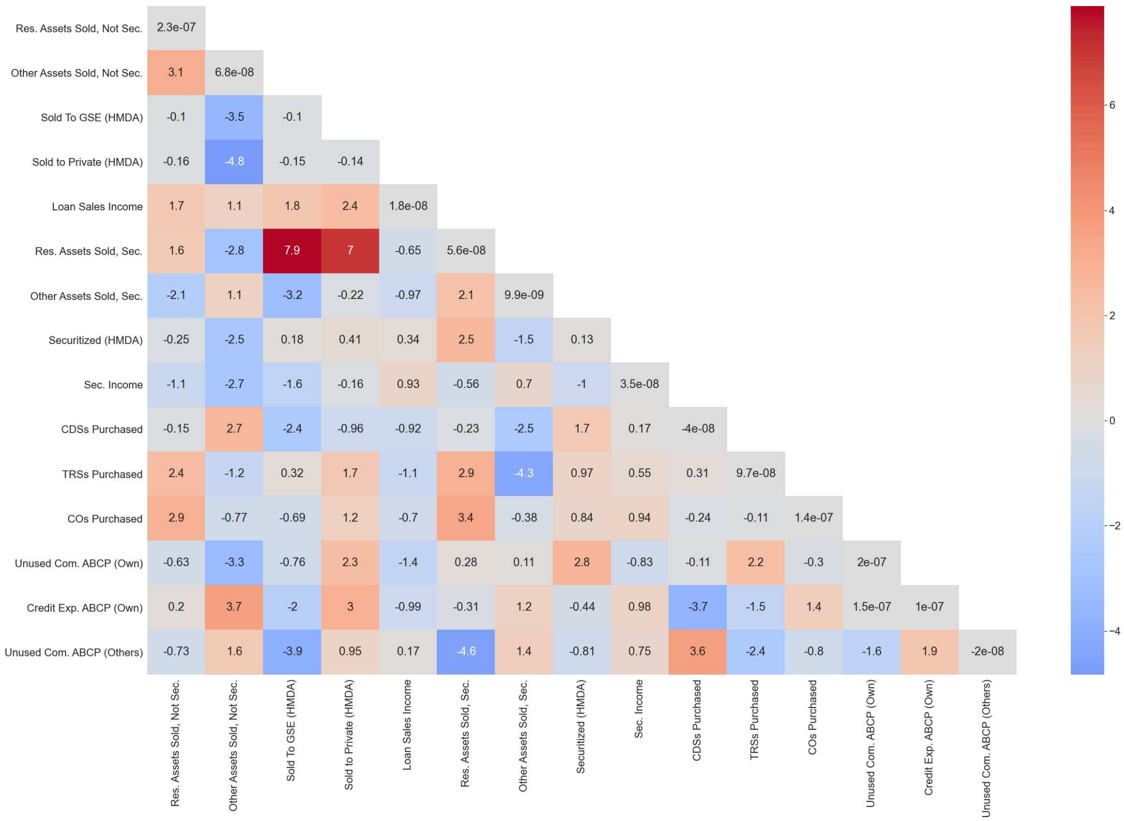
Notes. Pearson's correlation coefficient. All bold-face correlation coefficients are significant on the 5%-level.

Figure 6: Standardized Residuals First-Order Model



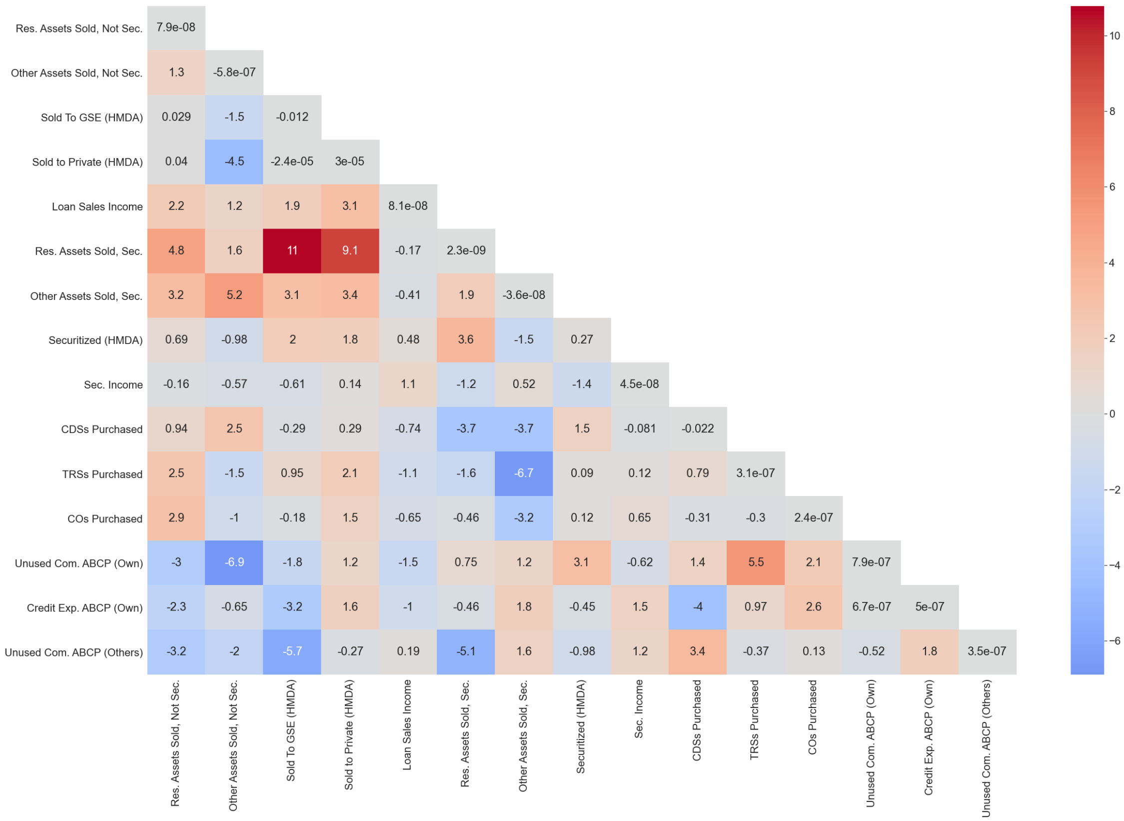
Notes. Standardized residuals of the first-order hypothesized model.

Figure 7: Standardized Residuals Respecified First-Order Model



Notes. Standardized residuals of the respecified first-order model.

Figure 8: Standardized Residuals Respecified Second-Order Model



Notes. Standardized residuals of the respecified second-order model.

Table 1: Overview of Securitization Studies and Their Proxies (2007–2020)

Authors	Research Focus	Scope	Data Source	Securitization Indicator
Abdelsalam et al. (2021)	Organizational and geographical religiosity as driver of securitization	Islamic World; 2009	BankFocus and Orbis (Bank Level)	Securitization dummy based on the principle balance of assets sold and securitized
Acharya et al. (2013)	Analysis of the structure of risk sharing between ABCP conduits and sponsoring banks	U.S.; 2001–2009	Moody's, Bankscope (Bank Level)	Total ABCPs outstanding; liquidity guarantees to ABCP-conduits; credit guarantees to ABCP-conduits
Acharya et al. (2017)	Analysis of how banks obtained liquidity in response to ABCP-market freezes	U.S.; 2007	FR Y-9C; Call Reports (BHC level)	Total ABCPs outstanding
Affinito and Tagliaferri (2010)	Why do banks securitize their loans?	Italy; 2000-2006	Italian Central Credit Register; Bank of Italy's Accounting Supervisory Reports (Loan Level)	Loans securitized: dummy and continuous variable
Agarwal et al. (2012)	Why do banks securitize their loans?	U.S.; 2004–2007	LPS Applied Analytics; Loan-Performance; HMDA (Loan Level)	Dummy for loan used for securitization
Albertazzi et al. (2015)	Securitization and asymmetric information	Italy; 1996–2006	Bank of Italy (Loan Level)	Dummy for mortgage used for securitization

Table 1 *(continued)*

Authors	Reseach Focus	Scope	Data Source	Securitization Indicator
Altunbas et al. (2019)	The effect of securitization and bank capital on bank competition	Euro-area; 2003–2009	Dealogic Bondware (Transaction Level)	Accumulated flows of securities from own securitization: MBSs, ABSs, CDOs
Aysun and Hepp (2011)	Securitization and the balance sheet channel of monetary transmission	U.S.; 2001–2009	Call Reports (Bank Level)	Principle balance of assets sold and securitized: split in several categories
Beccalli et al. (2015)	The effect of securitization on banks' leverage cyclicality	U.S.; 2001–2010	FR Y-9C (BHC Level)	Principle balance of assets sold and securitized
Bayeh et al. (2021)	Securitization, competition, and efficiency	U.S.; 2001–2019	Call Reports (Bank Level)	Securitization dummy based on the principle balance of assets sold and securitized
Benmelech et al. (2012)	The effect of securitization on loan performance	1997–2007	Standard and Poor's Quarterly CDO Deal List; Creditflux (Transaction Level)	Loans used in collateralized loan obligations (CLOs); CLOs issued

Table 1 *(continued)*

Authors	Reseach Focus	Scope	Data Source	Securitization Indicator
Bertay et al. (2017)	The effect of securitization on economic activity	World; 2007–2008	AB Alert; CM Alert (Country Level)	Securities resulting from securitization issued
Cardone-Riportella et al. (2010)	Why do banks securitize their loans?	Spain; 2000–2007	Bankscope, Bank of Spain (Bank Level)	Level of securities resulting from securitization issued
Casu et al. (2011)	Does securitization reduce credit risk taking?	U.S.; 2001–2007	FR Y-9C (BHC Level)	Principle balance of assets sold and securitized
Casu et al. (2013)	The effect of securitization on bank performance	U.S.; 2001–2008	Call Reports (Bank Level)	Principle balance of assets sold and securitized: level and dummy
Chen et al. (2019)	The effect of management expertise on securitization policies	U.S.; 2001–2011	FR Y-9C (BHC Level)	Principle balance of assets sold and securitized
Cheng et al. (2011)	Securitization and asymmetric information	U.S.; 2001–2007	FR Y-9C (BHC Level)	Principle balance of assets sold and securitized
Dell'ariccia et al. (2012)	The effect of securitization on lending standards	U.S.; 2000–2006	HMDA (Loan Level)	Dummy for loan used for securitization

Table 1 *(continued)*

Authors	Reseach Focus	Scope	Data Source	Securitization Indicator
Dionne and Harchaoui (2008)	The effect of securitization on bank risk taking	Canada; 1988–1998	Canadian Banking Association (Bank Level)	Principle balance of assets sold and securitized
Elul (2016)	The effect of securitization on loan performance	U.S.; 2005–2006	LPS Applied Analytics (Loan Level)	Investor type of the loan: private-securitized and several GSEs
Farruggio and Uhde (2015)	Drivers of securitization	Europe; 1997–2010	Moody's, Standard & Poor's'; FitchRating; BankScope (Bank Level)	Principle balance of assets sold and securitized: level and dummy
Franke and Krahnen (2007)	The effect of securitization on risk sharing	Europe; 2003	Moody's European Securitization List (Transaction Level)	Securities resulting from securitization issued: CLOs, CBOs, and CDOs
Haensel and Krahnen (2011)	The effect of securitization on bank risk taking	Europe; 2004–2005	Standard and Poor's Quarterly CDO Deal List (Transaction Level)	CDO transactions
Han et al. (2015)	The effect of corporate taxes on securitization	U.S.; 2001–2008	HMDA (Loan Level)	Dummy for loan used for securitization

Table 1 *(continued)*

Authors	Reseach Focus	Scope	Data Source	Securitization Indicator
Kara et al. (2019)	The effect of securitization on credit quality	Euro-area; 2005–2007	Dealogic-Loanware (Loan Level)	Securities resulting from securitization issued: CLOs
Keys et al. (2009)	The effect of financial regulation on securitization	U.S.; 2001–2006	LoanPerformance (Loan Level)	Dummy for loan used for securitization
Keys et al. (2010)	The effect of securitization on banks' screening practices	U.S.; 2001–2006	LoanPerformance (Loan Level)	Dummy for loan used for securitization
Kisin and Manela (2016)	Shadow costs of capital requirements	U.S.; 2002–2012	Moody's (Bank Level)	Total assets ABCPs conduits; liquidity provisions to ABCPs conduits
Klee and Shin (2020)	Securitization and asymmetric information	U.S.; 2017–2019	SEC Regulation AB files (Loan/Transaction Level)	Securities resulting from securitization issued: Auto ABSs
Klein et al. (2021)	Securitization and agency problems	Europe; 2012–2017	European DataWarehouse (Loan Level)	SME loans that serve as collateral in ABSs
Krainer and Laderman (2014)	The effect of securitization on loan performance	U.S.; 2000–2007	LPS Applied Analytics (Loan Level)	Investor type of the loan: private-securitized and several GSEs

Table 1 *(continued)*

Authors	Reseach Focus	Scope	Data Source	Securitization Indicator
Kuncl (2019)	The effect of recourse on information asymmetry in the securitization process over the business cycle	Europe; 1998–2013	Moody's Performance Data Services (Loan Level)	Securities resulting from securitization issued: RMBSs
Le et al. (2016)	The effect of securitization on bank risk taking	U.S.; 2001–2012	FR Y-9C (BHC Level)	Principle balance of assets sold and securitized: level and dummy
Loutskina (2011)	The effect of securitization on banks' liquidity and funding management	U.S.; 1976–2007	Call Reports (Bank Level)	Principle balance of assets sold and securitized
Lützenkirchen et al. (2014)	The effect of securitization on the cyclicality of regulatory capital	2007–2008	Moody's (Tranche Level)	Securities resulting from securitization issued: CDOs, ABSs, RMBSs, HELs, CMBSs
Maddaloni and Peydró (2011)	Securitization, risk taking and low interest rates	U.S./Europe; 1991-2008	BLS/SLO (Bank Level)	Securities resulting from securitization issued: ABSs, MBSs
Michalak and Uhde (2012)	The effect of securitization on bank stability	Europe; 1997–2007	Moody's, Standard & Poor's'; FitchRating; BankScope (Bank Level)	Securities resulting from securitization issued: cash, synthetic

Table 1 *(continued)*

Authors	Reseach Focus	Scope	Data Source	Securitization Indicator
Nijskens and Wagner (2011)	The effect of securitization on systemic risk	U.S.; 1996–2004	Datastream, Call Reports (Bank Level)	Securities resulting from securitization issued: CLOs, CDSs
Purnanandam (2011)	The effect of securitization on loan quality	U.S.; 2006–2008	Call Reports; HMDA (Bank Level)	Purchaser type of the loan
Trapp and Weiß (2016)	The effect of securitization on extreme equity returns	U.S.; 2006	SEC 10-K Filings	Dummy for loan securitization
Uhde and Michalak (2010)	The effect of securitization on systematic risk	Europe; 1997–2007	Moody's; Standard & Poor's; FitchRatings (Transaction Level)	Securities resulting from securitization issued: CDOs, RMBSs, CMBSs
Uhde (2020)	Tax avoidance and securitization	Europe; 1997–2010	Moody's; Standard & Poor's; FitchRatings (Transaction Level)	Securities resulting from securitization issued: CDOs, RMBSs, CMBSs
Uzun and Webb (2007)	The effect of securitization on bank characteristics and capital arbitrage	U.S.; 2001–2005	Call Reports (Bank Level)	Principle balance of assets sold and securitized

Notes. A non-comprehensive list of studies focused on various aspects of securitization from 2007 onwards. The literature uses many different proxies on many different levels for securitization.

Table 2: Possible Proxies for Securitization

Name	Captures	Source	Data Source	Variables
Residential Assets sold and not securitized (with recourse; X_1)	Loan Sales	Based on Irani and Meisenzahl (2017)	Call Reports; RC-S	B790
Assets sold and not securitized (with recourse; X_2)	Loan Sales	Based on Irani and Meisenzahl (2017)	Call Reports; RC-S	B791–B796
Loans sold to Government-Sponsered Entities (GSEs), not securitized (X_3)	Loan Sales	Used by Agarwal et al. (2012) and Han et al. (2015)	HMDA	Variable purchaser $\in \{1, 2, 3, 31, 32, 4\}$
Loans Sold to private institutions, not securitized (X_4)	Loan Sales	Used by Agarwal et al. (2012) and Han et al. (2015)	HMDA	Variable purchaser $\in \{6, 7, 8\}$
Loan Sales Income (X_5)	Loan Sales	New	Call Reports; RI	5416
Small Business Obligations Transferred With Recourse (X_6)	ABS/CDO securitization/Loan Sales	New; similar to assets sold and (not) securitized	Call Reports; RC-S	A249
Residential Loans sold and securitized (with recourse; X_7)	ABS securitization	Used by Aysun and Hepp (2011), Casu et al. (2013), and Uzun and Webb (2007)	Call Reports; RC-S	B705

Table 2 *(continued)*

Name	Captures	Source	Data Source	Variables
Other Assets sold and securitized (with recourse; X_8)	ABS securitization	Used by Aysun and Hepp (2011), Casu et al. (2013), and Uzun and Webb (2007)	Call Reports; RC-S	B706–B711
Loans sold and securitized (X_9)	Loan Sales	Used by Agarwal et al. (2012), Dell'ariccia et al. (2012), and Han et al. (2015)	HMDA	Variable purchaser = 5
Securitization Income (X_{10})	ABS/CDO securitization	New	Call Reports; RI	B493
Servicing Fees (X_{11})	ABS/CDO/ABCP securitization/Loan Sales	New	Call Reports; RI	B492
Credit Default Swaps Purchased (X_{12})	CDO securitization (Synthetic)	Based on Lancaster et al. (2008) and Nijskens and Wagner (2011)	Call Reports; RC-L	C969
Total Return Swaps Purchased (X_{13})	CDO securitization (Synthetic)	Based on Lancaster et al. (2008) and Nijskens and Wagner (2011)	Call Reports; RC-L	C971
Credit Options Purchased (X_{14})	CDO securitization (Synthetic)	Based on Lancaster et al. (2008) and Nijskens and Wagner (2011)	Call Reports; RC-L	C973
Unused Commitments to Provide Liquidity to Own ABCP Conduits (X_{15})	ABCP securitization	Based on Acharya et al. (2013)	Call Reports; RC-S	B808, B809

Table 2 *(continued)*

Name	Captures	Source	Data Source	Variables
Maximum credit Exposure to Own ABCP Conduits (X_{16})	ABCP securitization	Based on Acharya et al. (2013)	Call Reports; RC-S	B806, B807
Unused Commitments to Provide Liquidity to ABCP Conduits From Others (X_{17})	ABCP securitization	Based on Acharya et al. (2013)	Call Reports; RC-S	B808, B809
Maximum credit Exposure to ABCP Conduits From Others (X_{18})	ABCP securitization	Based on Acharya et al. (2013)	Call Reports; RC-S	B806, B807

Notes. Table contains multiple potential proxies for securitization. All proxies come from the Call Reports or the HMDA. The proxies in the list are not used by the literature (new), based on the literature, or used by the literature. The HMDA include a variable 'purchaser' that indicates if a loan is sold, securitized or not; each value of the variable indicates a sale to a particular party, or private securitization. We have included the Call Report schedule where available.

Table 3: Summary Statistics Securitization Proxies

	Mean	SD	Median	75%	95%	99%
Res. Assets Sold, Not Sec.	61561.8	892299.2	0.0	227.0	103282.2	633939.3
Other Assets Sold, Not Sec.	123658.4	1362051.6	0.0	0.0	371.6	3851257.3
Sold To GSE (HMDA)	590551.4	6428656.1	0.0	31692.2	844113.0	10627917.3
Sold to Private (HMDA)	257940.1	2538977.8	10398.5	87823.0	559754.3	3295998.3
Loan Sales Income	13074.7	105022.6	1046.0	3963.8	39136.3	328260.0
Res. Assets Sold, Sec.	1394190.7	19084206.5	0.0	0.0	1344.3	15535887.6
Other Assets Sold, Sec.	506140.6	6111372.5	0.0	0.0	0.0	4315744.7
Securitized (HMDA)	34464.2	1789524.9	0.0	0.0	129.1	124665.4
Sec. Income	8808.6	164252.7	0.0	0.0	0.0	21213.3
SBO Sold	803.8	27434.7	0.0	0.0	0.0	0.0
CDSs Purchased	9512433.0	135272516.0	0.0	0.0	0.0	23783120.0
TRSs Purchased	133455.9	1529285.6	0.0	0.0	0.0	2398400.0
COs Purchased	121854.6	2207544.5	0.0	0.0	0.0	0.0
Unused Com. ABCP (Own)	200558.7	3041031.3	0.0	0.0	0.0	1836610.0
Credit Exp. ABCP (Own)	28146.1	493799.3	0.0	0.0	0.0	1190.2
Unused Com. ABCP (Others)	14962.3	229700.5	0.0	0.0	0.0	193000.0
Credit Exp. ABCP (Others)	1176.5	36902.4	0.0	0.0	0.0	0.0
Net Servicing Fees	22889.1	230497.4	37.0	737.8	17226.6	555422.2

Notes. Summary statistics of the securitization proxies. All numbers are in thousands USD. 75%, 95% and 99% are the 75th, 95th and 99th percentile, respectively.

Table 4: Number of Securitizers Per Proxy

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
N	466	484	487	490	489	492	512	517	535	557	586	600	623
Res. Assets Sold, Not Sec.	101	118	118	123	126	129	144	149	158	169	171	183	199
Other Assets Sold, Not Sec.	33	35	42	34	32	29	37	40	40	39	36	38	39
Sold To GSE (HMDA)	189	189	181	199	206	199	212	219	241	248	266	270	266
Sold to Private (HMDA)	319	329	328	322	318	311	317	323	335	348	357	370	372
Loan Sales Income	353	378	377	381	400	397	416	431	448	455	482	488	506
Res. Assets Sold, Sec.	31	29	27	27	29	27	29	25	28	32	34	34	33
Other Assets Sold, Sec.	41	39	37	32	19	19	20	16	19	21	22	20	21
Securitized (HMDA)	34	31	18	18	33	28	32	31	33	32	27	22	31
Sec. Income	37	34	25	22	7	4	6	9	7	7	8	15	16
SBO Sold	6	7	5	4	7	5	5	4	4	4	4	5	0
CDSs Purchased	23	22	23	22	17	17	19	18	16	18	18	16	19
TRSs Purchased	8	10	13	10	11	9	10	10	8	8	8	8	9
COs Purchased	4	6	5	5	5	4	5	4	4	5	5	4	4
Unused Com. ABCP (Own)	16	15	13	8	7	6	7	5	4	4	4	4	3
Credit Exp. ABCP (Own)	14	12	9	7	5	4	4	4	4	3	3	3	3
Unused Com. ABCP (Others)	12	13	10	9	10	10	8	6	4	4	4	4	3
Credit Exp. ABCP (Others)	7	9	5	4	1	1	0	0	0	0	0	0	0
Net Servicing Fees	288	287	285	285	292	292	303	322	342	360	376	397	415

Notes. The number of securitizers per proxy per year.

Table 5: Results Explanatory Factor Analysis: Four and Five Factor Models

	Four Factor Model				Five Factor Model				
	F1	F2	F3	F4	F1	F2	F3	F4	F5
Res. Assets Sold, Not Sec.	-0.0606	**0.7157**	-0.0374	0.0958	-0.0463	**0.7003**	-0.0106	0.048	0.0405
Other Assets Sold, Not Sec.	0.2639	0.2009	0.2734	*0.3297*	0.2173	0.1567	0.2924	0.2096	0.2677
Sold To GSE (HMDA)	-0.1467	**0.7721**	0.005	0.019	-0.1299	**0.752**	0.0437	-0.0202	0.0045
Sold to Private (HMDA)	-0.1216	**0.8298**	-0.202	0.0176	-0.0846	**0.8311**	-0.1786	0.0175	-0.0711
Loan Sales Income	-0.0096	0.0497	-0.3048	**0.7871**	-0.0503	0.0452	-0.3877	**0.8976**	0.0496
Res. Assets Sold, Sec.	*0.3882*	0.27	0.2557	0.0572	*0.3615*	0.2347	0.2974	0.0054	0.0764
Other Assets Sold, Sec.	*0.3814*	0.0784	**0.4622**	0.1014	*0.3226*	0.0191	**0.5135**	0.0592	0.1014
Securitized (HMDA)	0.1155	0.2718	0.0019	-0.1943	0.1266	0.2668	0.0272	-0.0546	-0.2872
Sec. Income	-0.0744	-0.1038	*0.3449*	0.0529	-0.1429	-0.164	*0.3507*	**0.4412**	-0.5243
SBO Sold	-0.0451	-0.005	0.1354	**0.4513**	-0.0656	-0.0178	0.1174	0.0513	**0.7363**
CDSs Purchased	**0.8294**	-0.0373	0.0708	0.0082	**0.8104**	-0.0427	0.0966	0.0042	-0.0074
TRSs Purchased	**0.8836**	-0.0778	-0.0882	-0.16	**0.8886**	-0.0599	-0.0635	-0.1031	-0.156
COs Purchased	**0.8331**	-0.1031	-0.0199	-0.1496	**0.831**	-0.0925	0.0023	-0.0781	-0.165
Unused Com. ABCP (Own)	**0.8673**	-0.0338	-0.0561	-0.0691	**0.8714**	-0.0183	-0.0272	-0.154	0.078
Credit Exp. ABCP (Own)	**0.8372**	-0.0583	-0.0659	0.0311	**0.8328**	-0.0459	-0.0502	-0.0255	0.069
Unused Com. ABCP (Others)	**0.7922**	-0.1002	-0.1978	0.1848	**0.7857**	-0.0795	-0.2172	0.2099	-0.0063
Net Servicing Fees	-0.1313	-0.024	**0.9039**	-0.3377	-0.1924	-0.1134	**0.9961**	-0.3687	0.0062

Notes. Factor loadings based on the oblique promax rotation. The explanatory factor models are estimated by a principal factor algorithm implemented by FactorAnalyzer in Python. The principal factor algorithm is more robust to deviations from normal than a maximum likelihood algorithm. The first four columns contain the factor loadings from a four factor model with all proxies. The next five columns present the factor loadings of a five factor model. The number of original factors are determined by a parallel analysis and the rule of thumb eigenvalue > 0. Factor loadings are in boldface if they are greater than 0.4, and in italics if they are between 0.3 and 0.4.

Table 6: Goodness-of-Fit Indices

Fit Measure	Computation	Cut-off	Source
χ^2	$F_{ML}(N-1)$	$p < 0.05$	(Brown, 2015; Hoyle, 2012)
Goodness of Fit (GFI)*	$1-(\boldsymbol{e'We})/(\boldsymbol{s'Ws})$	> 0.95	(Hoyle, 2012)
Adjusted Goodness of Fit (AGFI)*	$1-p^*/df(1-GFI)$	> 0.95	(Hoyle, 2012)
Normed Fit Index (NFI)	$(\chi^2_B-\chi^2_T)/\chi^2_B$	> 0.95	(Hu and Bentler, 1999)
Tucker–Lewis Index (TLI)	$[(\chi^2_B - df_B) - (\chi^2_T - df_T)]/[(\chi^2_B - df_B) - 1]$	Acceptable: > 0.90; Good: > 0.95	(Bentler, 1990; Brown, 2015)
Comparative Fit Index (CFI)	$1 - max[(\chi^2_T - df_T), 0]/max[(\chi^2_T - df_T), (\chi^2_B - df_B), 0]$	Acceptable: > 0.90; Good: > 0.95	(Bentler, 1990; Brown, 2015)
Root Mean Square Error of Approximation (RMSEA)	$SQRT(d/df) = SQRT((\chi^2 - df/N)/df)$	Close to or below 0.06	(Brown, 2015; Hoyle, 2012)
Standardized Root Mean Square Residual (SRMR)	$p^{*-1}(\boldsymbol{e'W_s e})$	< 0.08	(Brown, 2015; Hoyle, 2012)
Incremental Fit Index (IFI)	$(\chi^2_B-\chi^2_T)/(\chi^2_B-df_T)$	> 0.95	(Hoyle, 2012)
Relative Non-centrality Index (RNI)	$[(\chi^2_B - df_B) - (\chi^2_T - df_T)]/(\chi^2_B - df_B)$	> 0.95	(Hoyle, 2012)

Notes. Fit indices used and their respective cut-off points. Where $\boldsymbol{W}$ is a weight matrix, $\boldsymbol{W_s}$ is a diagonal weight matrix, $\boldsymbol{e}$ is a vector of residuals from the covariance matrix, $\boldsymbol{s}$ is a vector of non-redundant elements in the observed covariance matrix, and p^* is the number of non-duplicated elements in the covariance matrix * These fit indices are very sensitive to sample size. Especially the GFI increases in the number of parameters and is upward biased in large samples. We only include these indices in our analysis, but do not rely exclusively on them.

Table 7: Fit Indices: First-Order Model

	Index
No. Params	45.0000
DoF	75.0000
χ^2	2653.4220
p-val χ^2	0.0000
χ^2 (scaled)	437.2677
p-val χ^2 (scaled)	0.0000
χ^2 scaling factor	6.0682
DoF baseline	105.0000
χ^2 baseline	34977.4246
p-val χ^2 baseline	0.0000
χ^2 baseline (scaled)	4457.1988
p-val χ^2 baseline (scaled)	0.0000
χ^2 baseline scaling factor	7.8474
GFI	0.9510
AGFI	0.9215
NFI	0.9241
TLI (robust)	0.9099
CFI (robust)	0.9356
RMSEA (robust)	0.0655
RMSEA lower bound (robust)	0.0596
RMSEA upper bound (robust)	0.0715
SRMR	0.0341
IFI	0.9261
RNI (robust)	0.9356
AIC	377110.4387
BIC	377417.8000

Notes. Fit indices of the first-order model.

Table 8: Fit Indices: Respecified Model Model

	First-Order	Second-Order
No. Params	46.0000	45.0000
DoF	74.0000	75.0000
χ^2	1986.0548	2475.6300
p-val χ^2	0.0000	0.0000
χ^2 (scaled)	330.3093	404.2512
p-val χ^2 (scaled)	0.0000	0.0000
χ^2 scaling factor	6.0127	6.1240
DoF baseline	105.0000	105.0000
χ^2 baseline	34977.4246	34977.4246
p-val χ^2 baseline	0.0000	0.0000
χ^2 baseline (scaled)	4457.1988	4457.1988
p-val χ^2 baseline (scaled)	0.0000	0.0000
χ^2 baseline scaling factor	7.8474	7.8474
GFI	0.9630	0.9554
AGFI	0.9400	0.9287
NFI	0.9432	0.9292
TLI (robust)	0.9360	0.9173
CFI (robust)	0.9549	0.9410
RMSEA (robust)	0.0552	0.0627
RMSEA lower bound (robust)	0.0492	0.0568
RMSEA upper bound (robust)	0.0613	0.0688
SRMR	0.0298	0.0375
IFI	0.9452	0.9312
RNI (robust)	0.9549	0.9410
AIC	376445.0715	376932.6467
BIC	376759.2631	377240.0080

Notes. Fit indices of the respecified first- and second-order model.

Table 9: Parameter Estimates: Respecified First-Order Model

	Parameters	SD	Z-value	P-value	Parameters (std.)	Parameters (compl. std.)
$\lambda_{LS,1}$	1.0000	0.0000			1.4602	0.3345
$\lambda_{LS,2}$	1.2445	0.0955	13.0374	0.0000	1.8171	0.6972
$\lambda_{LS,3}$	1.1888	0.0879	13.5257	0.0000	1.7359	0.3128
$\lambda_{LS,4}$	0.7338	0.0590	12.4484	0.0000	1.0715	0.1981
$\lambda_{LS,5}$	0.0020	0.0112	0.1769	0.8596	0.0029	0.0160
$\lambda_{ABSCDO,7}$	1.0000	0.0000			2.0476	0.6644
$\lambda_{ABSCDO,8}$	0.9457	0.0443	21.3430	0.0000	1.9365	0.6843
$\lambda_{ABSCDO,9}$	0.2121	0.0355	5.9776	0.0000	0.4343	0.2026
$\lambda_{ABSCDO,10}$	0.0093	0.0044	2.1243	0.0336	0.0191	0.1047
$\lambda_{ABSCDO,12}$	0.4580	0.1020	4.4916	0.0000	0.9378	0.3412
$\lambda_{CD,12}$	1.0000	0.0000			1.4137	0.5144
$\lambda_{CD,13}$	1.1839	0.1570	7.5409	0.0000	1.6737	0.8817
$\lambda_{CD,14}$	0.7984	0.1223	6.5280	0.0000	1.1287	0.8085
$\lambda_{ABCP,15}$	1.0000	0.0000			1.4367	0.8018
$\lambda_{ABCP,16}$	0.7070	0.0670	10.5526	0.0000	1.0158	0.7423
$\lambda_{ABCP,17}$	0.6816	0.0803	8.4852	0.0000	0.9792	0.6458
$\lambda_{ABCP,10}$	-0.0082	0.0105	-0.7837	0.4332	-0.0118	-0.0647
$\lambda_{ABCP,12}$	0.1311	0.2230	0.5879	0.5566	0.1883	0.0685
$\delta_{3,4}$	8.1262	0.3384	24.0127	0.0000	8.1262	0.2907
$\delta_{3,9}$	0.9202	0.1658	5.5514	0.0000	0.9202	0.0831
$\delta_{4,9}$	0.7724	0.1397	5.5281	0.0000	0.7724	0.0694
$\delta_{7,9}$	0.2047	0.1372	1.4915	0.1358	0.2047	0.0423
$\delta_{1,3}$	4.2291	0.3316	12.7536	0.0000	4.2291	0.1950
$\delta_{1,4}$	6.8970	0.2584	26.6928	0.0000	6.8970	0.3162
$\delta_{15,16}$	0.3888	0.1119	3.4733	0.0005	0.3888	0.3960
$\delta_{1,1}$	16.9213	0.3422	49.4423	0.0000	16.9213	0.8881
$\delta_{2,2}$	3.4904	0.2829	12.3373	0.0000	3.4904	0.5139
$\delta_{3,3}$	27.7896	0.3878	71.6665	0.0000	27.7896	0.9022
$\delta_{4,4}$	28.1179	0.2267	124.0047	0.0000	28.1179	0.9608
$\delta_{5,5}$	0.0326	0.0304	1.0721	0.2837	0.0326	0.9997
$\delta_{7,7}$	5.3065	0.3457	15.3484	0.0000	5.3065	0.5586
$\delta_{8,8}$	4.2590	0.3344	12.7371	0.0000	4.2590	0.5318
$\delta_{9,9}$	4.4089	0.2425	18.1803	0.0000	4.4089	0.9590
$\delta_{10,10}$	0.0331	0.0276	1.2001	0.2301	0.0331	0.9957
$\delta_{12,12}$	2.1812	0.1939	11.2468	0.0000	2.1812	0.2888
$\delta_{13,13}$	0.8022	0.1272	6.3047	0.0000	0.8022	0.2226
$\delta_{14,14}$	0.6749	0.0867	7.7800	0.0000	0.6749	0.3463
$\delta_{15,15}$	1.1465	0.1913	5.9930	0.0000	1.1465	0.3571
$\delta_{16,16}$	0.8409	0.1171	7.1782	0.0000	0.8409	0.4490
$\delta_{17,17}$	1.3403	0.1512	8.8666	0.0000	1.3403	0.5830
$\phi_{LS,LS}$	2.1321	0.2747	7.7618	0.0000	1.0000	1.0000
$\phi_{ABSCDO,ABSCDO}$	4.1928	0.4609	9.0963	0.0000	1.0000	1.0000
$\phi_{CD,CD}$	1.9986	0.5935	3.3676	0.0008	1.0000	1.0000
$\phi_{ABCP,ABCP}$	2.0641	0.3332	6.1954	0.0000	1.0000	1.0000
$\phi_{LS,ABSCDO}$	2.7380	0.2668	10.2631	0.0000	0.9157	0.9157
$\phi_{LS,CD}$	0.8294	0.1911	4.3393	0.0000	0.4018	0.4018
$\phi_{LS,ABCP}$	1.2572	0.1780	7.0639	0.0000	0.5993	0.5993
$\phi_{ABSCDO,CD}$	1.9040	0.3582	5.3155	0.0000	0.6577	0.6577
$\phi_{ABSCDO,ABCP}$	2.3536	0.3001	7.8430	0.0000	0.8001	0.8001
$\phi_{CD,ABCP}$	1.6483	0.3298	4.9978	0.0000	0.8115	0.8115

Notes. Parameter estimates, factor variances and indicator variances of the respecified factor model without a nested securitization structure. The improved model is similar to the non-nested model but without the CDO factor and without servicing fees.The second to last column contains the standardized parameter estimates, where the factor variances are fixed to one. The last column presents the completely standardized parameter estimates, where the factor variances are fixed to one and all other parameters are standardized.

Table 10: Communalities: Respecified First-Order Model

	Communality
Res. Assets Sold, Not Sec.	0.1119
Other Assets Sold, Not Sec.	0.4861
Sold To GSE (HMDA)	0.0978
Sold to Private (HMDA)	0.0392
Loan Sales Income	0.0003
Res. Assets Sold, Sec.	0.4414
Other Assets Sold, Sec.	0.4682
Securitized (HMDA)	0.0410
Sec. Income	0.0043
CDSs Purchased	0.7112
TRSs Purchased	0.7774
COs Purchased	0.6537
Unused Com. ABCP (Own)	0.6429
Credit Exp. ABCP (Own)	0.5510
Unused Com. ABCP (Others)	0.4170

Notes. Communalities of the respecified first-order model.

Table 11: Parameter Estimates: First-Order Model

	Parameters	SD	Z-value	P-value	Parameters (std.)	Parameters (compl. std.)
$\lambda_{LS,1}$	1.0000	0.0000			1.5113	0.3462
$\lambda_{LS,2}$	1.1531	0.0886	13.0184	0.0000	1.7427	0.6687
$\lambda_{LS,3}$	1.1947	0.0910	13.1349	0.0000	1.8055	0.3253
$\lambda_{LS,4}$	0.7525	0.0595	12.6572	0.0000	1.1373	0.2102
$\lambda_{LS,5}$	0.0009	0.0119	0.0733	0.9416	0.0013	0.0073
$\lambda_{ABS,7}$	1.0000	0.0000			2.1118	0.6852
$\lambda_{ABS,8}$	0.9253	0.0423	21.8822	0.0000	1.9541	0.6905
$\lambda_{ABS,9}$	0.2071	0.0349	5.9309	0.0000	0.4375	0.2040
$\lambda_{ABS,10}$	0.0103	0.0039	2.6413	0.0083	0.0219	0.1198
$\lambda_{CDO,12}$	1.0000	0.0000			2.3177	0.8433
$\lambda_{CDO,13}$	0.6933	0.0234	29.6017	0.0000	1.6069	0.8465
$\lambda_{CDO,14}$	0.4768	0.0396	12.0359	0.0000	1.1051	0.7916
$\lambda_{CDO,10}$	0.0096	0.0169	0.5679	0.5701	0.0222	0.1219
$\lambda_{ABCP,15}$	1.0000	0.0000			1.4433	0.8055
$\lambda_{ABCP,16}$	0.7081	0.0685	10.3433	0.0000	1.0220	0.7468
$\lambda_{ABCP,17}$	0.6738	0.0795	8.4747	0.0000	0.9725	0.6414
$\lambda_{ABCP,10}$	-0.0245	0.0343	-0.7153	0.4744	-0.0354	-0.1941
$\delta_{3,4}$	7.9334	0.3371	23.5360	0.0000	7.9334	0.2858
$\delta_{3,9}$	0.9084	0.1662	5.4644	0.0000	0.9084	0.0825
$\delta_{4,9}$	0.7630	0.1397	5.4608	0.0000	0.7630	0.0687
$\delta_{7,9}$	0.1787	0.1364	1.3101	0.1901	0.1787	0.0379
$\delta_{1,3}$	4.0364	0.3353	12.0368	0.0000	4.0364	0.1878
$\delta_{1,4}$	6.7439	0.2574	26.1955	0.0000	6.7439	0.3114
$\delta_{15,16}$	0.3731	0.1064	3.5055	0.0005	0.3731	0.3861
$\delta_{1,1}$	16.7694	0.3509	47.7892	0.0000	16.7694	0.8801
$\delta_{2,2}$	3.7554	0.2965	12.6673	0.0000	3.7554	0.5529
$\delta_{3,3}$	27.5431	0.4161	66.1960	0.0000	27.5431	0.8942
$\delta_{4,4}$	27.9736	0.2273	123.0532	0.0000	27.9736	0.9558
$\delta_{5,5}$	0.0326	0.0304	1.0740	0.2828	0.0326	0.9999
$\delta_{7,7}$	5.0396	0.3307	15.2385	0.0000	5.0396	0.5305
$\delta_{8,8}$	4.1905	0.3302	12.6901	0.0000	4.1905	0.5232
$\delta_{9,9}$	4.4074	0.2425	18.1776	0.0000	4.4074	0.9584
$\delta_{10,10}$	0.0329	0.0270	1.2162	0.2239	0.0329	0.9888
$\delta_{12,12}$	2.1817	0.2547	8.5667	0.0000	2.1817	0.2888
$\delta_{13,13}$	1.0214	0.1464	6.9771	0.0000	1.0214	0.2834
$\delta_{14,14}$	0.7277	0.0882	8.2484	0.0000	0.7277	0.3734
$\delta_{15,15}$	1.1275	0.1910	5.9040	0.0000	1.1275	0.3512
$\delta_{16,16}$	0.8282	0.1148	7.2163	0.0000	0.8282	0.4423
$\delta_{17,17}$	1.3534	0.1532	8.8348	0.0000	1.3534	0.5886
$\phi_{LS,LS}$	2.2840	0.2932	7.7901	0.0000	1.0000	1.0000
$\phi_{ABS,ABS}$	4.4598	0.4570	9.7583	0.0000	1.0000	1.0000
$\phi_{CDO,CDO}$	5.3719	0.5020	10.7004	0.0000	1.0000	1.0000
$\phi_{ABCP,ABCP}$	2.0830	0.3355	6.2085	0.0000	1.0000	1.0000
$\phi_{LS,ABS}$	2.9079	0.2712	10.7230	0.0000	0.9111	0.9111
$\phi_{LS,CDO}$	1.8387	0.2426	7.5804	0.0000	0.5249	0.5249
$\phi_{LS,ABCP}$	1.3353	0.1837	7.2693	0.0000	0.6122	0.6122
$\phi_{ABS,CDO}$	3.5956	0.4017	8.9512	0.0000	0.7346	0.7346
$\phi_{ABS,ABCP}$	2.3865	0.3013	7.9211	0.0000	0.7830	0.7830
$\phi_{CDO,ABCP}$	2.8771	0.3629	7.9271	0.0000	0.8601	0.8601

Notes. Parameter estimates, factor variances and indicator variances of the factor model without a second-order securitization structure. All factors are allowed to correlate. The second to last column contains the standardized parameter estimates, where the factor variances are fixed to one. The last column presents the completely standardized parameter estimates, where the factor variances are fixed to one and all other parameters are standardized.

Table 12: Modification Indices: First-Order Model

	Mod. Indices	EPC	EPC (std.)	EPC (compl. std.)
$\lambda_{LS,12}$	680.7156	0.6586	0.9953	0.3621
$\lambda_{ABS,12}$	668.3576	0.5934	1.2531	0.4560
$\delta_{13,14}$	365.4978	0.3593	0.3593	0.4168
$\delta_{2,12}$	320.3866	0.8781	0.8781	0.3068
$\lambda_{ABCP,12}$	316.3650	1.0390	1.4995	0.5456
$\lambda_{ABS,13}$	299.8057	-0.2746	-0.5798	-0.3054
$\lambda_{LS,13}$	286.4363	-0.2950	-0.4458	-0.2349
$\delta_{12,17}$	226.0776	0.4115	0.4115	0.2395
$\delta_{2,15}$	192.1157	-0.4360	-0.4360	-0.2119
$\delta_{8,13}$	190.4098	-0.4668	-0.4668	-0.2256
$\delta_{2,16}$	180.0022	0.3253	0.3253	0.1845
$\delta_{14,16}$	156.7306	0.1271	0.1271	0.1638
$\delta_{13,15}$	155.7364	0.2034	0.2034	0.1896
$\delta_{12,14}$	149.8061	-0.3317	-0.3317	-0.2633
$\delta_{3,7}$	135.1972	1.8811	1.8811	0.1597
$\delta_{10,15}$	129.8500	-0.0302	-0.0302	-0.1571
$\delta_{14,15}$	118.9015	-0.1379	-0.1379	-0.1523
$\lambda_{CDO,16}$	108.5201	-0.1972	-0.4570	-0.3340
$\delta_{7,17}$	104.5346	-0.3928	-0.3928	-0.1504
$\lambda_{ABCP,13}$	104.2289	-0.4131	-0.5962	-0.3141
$\delta_{12,16}$	99.9275	-0.1885	-0.1885	-0.1402
$\delta_{2,14}$	99.8055	-0.2623	-0.2623	-0.1587
$\lambda_{LS,14}$	96.5630	-0.1285	-0.1943	-0.1391
$\delta_{2,13}$	91.2889	-0.3229	-0.3229	-0.1649
$\delta_{10,16}$	88.9518	0.0188	0.0188	0.1141

Notes. Modification indices of the first-order model. The second to last column contains the standardized modification indices, where the factor variances are fixed to one. The last column presents the completely standardized modification indices, where the factor variances are fixed to one and all other parameters are standardized.

Table 13: Modification Indices: Respecified First-Order Model

	Mod. Indices	EPC	EPC (std.)	EPC (compl. std.)
$\delta_{14,16}$	227.1085	0.1505	0.1505	0.1998
$\delta_{2,16}$	215.1286	0.3490	0.3490	0.2037
$\delta_{12,17}$	211.9625	0.4113	0.4113	0.2405
$\delta_{2,15}$	205.1180	-0.4436	-0.4436	-0.2217
$\delta_{12,16}$	177.4055	-0.2506	-0.2506	-0.1851
$\delta_{13,15}$	177.0645	0.2162	0.2162	0.2255
$\delta_{3,7}$	147.1209	1.9447	1.9447	0.1601
$\delta_{14,15}$	146.2038	-0.1516	-0.1516	-0.1723
$\delta_{10,15}$	134.5420	-0.0286	-0.0286	-0.1466
$\delta_{7,17}$	124.4323	-0.4298	-0.4298	-0.1611
$\lambda_{CD,15}$	111.0914	0.3166	0.4476	0.2498
$\delta_{8,13}$	105.8384	-0.3525	-0.3525	-0.1907
$\delta_{13,16}$	85.3688	-0.1178	-0.1178	-0.1435
$\lambda_{LS,15}$	84.4726	-0.1654	-0.2415	-0.1348
$\lambda_{CD,8}$	79.1367	-0.3921	-0.5544	-0.1959
$\delta_{9,15}$	77.9804	0.2402	0.2402	0.1069
$\delta_{15,17}$	75.7452	-0.1825	-0.1825	-0.1472
$\lambda_{ABCP,5}$	74.5057	-0.0210	-0.0302	-0.1673
$\delta_{2,12}$	71.5912	0.4743	0.4743	0.1719
$\lambda_{CD,16}$	69.9057	-0.1861	-0.2631	-0.1923
$\delta_{16,17}$	69.7619	0.1239	0.1239	0.1167
$\delta_{10,16}$	66.3520	0.0159	0.0159	0.0950
$\delta_{13,17}$	64.2223	-0.1491	-0.1491	-0.1438
$\lambda_{ABSCDO,5}$	59.0619	-0.0295	-0.0603	-0.3342
$\lambda_{LS,16}$	57.8244	0.1027	0.1500	0.1096

Notes. Modification indices of the respecified first-order model. The second to last column contains the standardized modification indices, where the factor variances are fixed to one. The last column presents the completely standardized modification indices, where the factor variances are fixed to one and all other parameters are standardized.

Table 14: Parameter Estimates: Respecified Second-Order Model

	Parameters	SD	Z-value	P-value	Parameters (std.)	Parameters (compl. std.)
$\lambda_{LS,1}$	1.0000	0.0000			1.4481	0.3318
$\lambda_{LS,2}$	1.3069	0.1106	11.8169	0.0000	1.8926	0.7262
$\lambda_{LS,3}$	1.1064	0.0866	12.7756	0.0000	1.6023	0.2888
$\lambda_{LS,4}$	0.7038	0.0623	11.3037	0.0000	1.0192	0.1884
$\lambda_{LS,5}$	0.0011	0.0116	0.0930	0.9259	0.0016	0.0087
$\lambda_{ABSCDO,7}$	1.0000	0.0000			2.0902	0.6782
$\lambda_{ABSCDO,8}$	0.9143	0.0435	21.0433	0.0000	1.9111	0.6753
$\lambda_{ABSCDO,9}$	0.2121	0.0362	5.8565	0.0000	0.4434	0.2069
$\lambda_{ABSCDO,10}$	0.0169	0.0064	2.6589	0.0078	0.0353	0.1937
$\lambda_{ABSCDO,12}$	0.3200	0.1476	2.1679	0.0302	0.6688	0.2433
$\lambda_{CD,12}$	1.0000	0.0000			1.1478	0.4176
$\lambda_{CD,13}$	1.4554	0.2185	6.6619	0.0000	1.6706	0.8800
$\lambda_{CD,14}$	0.9883	0.1656	5.9673	0.0000	1.1344	0.8126
$\lambda_{ABCP,15}$	1.0000	0.0000			1.3863	0.7737
$\lambda_{ABCP,16}$	0.7223	0.0649	11.1314	0.0000	1.0013	0.7317
$\lambda_{ABCP,17}$	0.7155	0.0793	9.0206	0.0000	0.9919	0.6541
$\lambda_{ABCP,10}$	-0.0194	0.0117	-1.6516	0.0986	-0.0269	-0.1473
$\lambda_{ABCP,12}$	0.5021	0.2738	1.8339	0.0667	0.6961	0.2533
$\phi_{SEC,ABSCDO}$	1.0000	0.0000			0.8905	0.8905
$\phi_{SEC,ABCP}$	0.6689	0.0520	12.8662	0.0000	0.8982	0.8982
$\delta_{3,4}$	8.3390	0.3404	24.4998	0.0000	8.3390	0.2955
$\delta_{3,9}$	0.9678	0.1674	5.7821	0.0000	0.9678	0.0869
$\delta_{4,9}$	0.7858	0.1400	5.6123	0.0000	0.7858	0.0706
$\delta_{7,9}$	0.1441	0.1385	1.0402	0.2983	0.1441	0.0303
$\delta_{1,3}$	4.4302	0.3293	13.4530	0.0000	4.4302	0.2025
$\delta_{1,4}$	6.9747	0.2575	27.0853	0.0000	6.9747	0.3189
$\delta_{15,16}$	0.4600	0.1284	3.5825	0.0003	0.4600	0.4344
$\delta_{1,1}$	16.9563	0.3401	49.8536	0.0000	16.9563	0.8899
$\delta_{2,2}$	3.2105	0.3556	9.0279	0.0000	3.2105	0.4727
$\delta_{3,3}$	28.2189	0.3811	74.0406	0.0000	28.2189	0.9166
$\delta_{4,4}$	28.2155	0.2331	121.0599	0.0000	28.2155	0.9645
$\delta_{5,5}$	0.0326	0.0304	1.0738	0.2829	0.0326	0.9999
$\delta_{7,7}$	5.1304	0.3644	14.0794	0.0000	5.1304	0.5401
$\delta_{8,8}$	4.3565	0.3702	11.7679	0.0000	4.3565	0.5439
$\delta_{9,9}$	4.3960	0.2412	18.2292	0.0000	4.3960	0.9572
$\delta_{10,10}$	0.0328	0.0275	1.1922	0.2332	0.0328	0.9864
$\delta_{12,12}$	2.2036	0.1933	11.3984	0.0000	2.2036	0.2917
$\delta_{13,13}$	0.8128	0.1253	6.4870	0.0000	0.8128	0.2255
$\delta_{14,14}$	0.6621	0.0851	7.7771	0.0000	0.6621	0.3397
$\delta_{15,15}$	1.2888	0.1925	6.6940	0.0000	1.2888	0.4014
$\delta_{16,16}$	0.8700	0.1228	7.0860	0.0000	0.8700	0.4646
$\delta_{17,17}$	1.3154	0.1519	8.6580	0.0000	1.3154	0.5721
$\phi_{LS,LS}$	2.0971	0.2729	7.6840	0.0000	1.0000	1.0000
$\phi_{ABSCDO,ABSCDO}$	0.9041	0.3227	2.8018	0.0051	0.2069	0.2069
$\phi_{CD,CD}$	1.3175	0.4417	2.9829	0.0029	1.0000	1.0000
$\phi_{ABCP,ABCP}$	0.3715	0.1611	2.3054	0.0211	0.1933	0.1933
$\phi_{SEC,SEC}$	3.4648	0.3806	9.1030	0.0000	1.0000	1.0000
$\phi_{LS,CD}$	0.6541	0.1592	4.1090	0.0000	0.3935	0.3935
$\phi_{LS,SEC}$	2.1934	0.2524	8.6892	0.0000	0.8137	0.8137
$\phi_{CD,SEC}$	1.7966	0.3351	5.3609	0.0000	0.8409	0.8409

Notes. Parameter estimates, factor variances and indicator variances of the factor model with a nested securitization structure. The factors ABS, CDO, ABCP are nested under a factor Securitization, which captures the general variance of securitization and equals the hypothesized factor model.The second to last column contains the standardized parameter estimates, where the factor variances are fixed to one. The last column presents the completely standardized parameter estimates, where the factor variances are fixed to one and all other parameters are standardized.

Table 15: Modification Indices: Respecified Second-Order Model Model

	Mod. Indices	EPC	EPC (std.)	EPC (compl. std.)
$\phi_{ABSCDO,CD}$	419.9162	-1.0300	-0.9438	-0.9438
$\phi_{LS,ABSCDO}$	419.9142	1.2575	0.9133	0.9133
$\phi_{LS,ABCP}$	419.9141	-0.8411	-0.9530	-0.9530
$\phi_{CD,ABCP}$	419.9117	0.6890	0.9848	0.9848
$\lambda_{CD,8}$	369.0574	-1.2036	-1.3815	-0.4882
$\lambda_{LS,15}$	355.7493	-0.4076	-0.5903	-0.3294
$\delta_{2,15}$	352.5740	-0.5941	-0.5941	-0.2921
$\lambda_{CD,15}$	311.7962	0.4780	0.5486	0.3062
$\lambda_{LS,8}$	275.2577	0.7753	1.1228	0.3967
$\delta_{14,16}$	260.6038	0.1590	0.1590	0.2094
$\delta_{13,15}$	236.0876	0.2473	0.2473	0.2416
$\delta_{12,16}$	229.0667	-0.2870	-0.2870	-0.2073
$\lambda_{SEC,17}$	193.4372	-1.2298	-2.2892	-1.5097
$\delta_{8,13}$	185.7325	-0.4782	-0.4782	-0.2541
$\delta_{3,7}$	184.2192	2.1063	2.1063	0.1751
$\lambda_{ABCP,2}$	145.5606	-1.1694	-1.6211	-0.6220
$\delta_{12,17}$	127.2400	0.3218	0.3218	0.1890
$\delta_{10,15}$	119.0487	-0.0278	-0.0278	-0.1350
$\delta_{7,17}$	106.8370	-0.3959	-0.3959	-0.1524
$\delta_{14,15}$	105.2579	-0.1280	-0.1280	-0.1386
$\delta_{2,16}$	101.7466	0.2477	0.2477	0.1482
$\delta_{2,12}$	101.0968	0.5028	0.5028	0.1890
$\delta_{10,16}$	87.9121	0.0184	0.0184	0.1090
$\delta_{9,15}$	78.6544	0.2446	0.2446	0.1028
$\delta_{2,8}$	77.1476	0.6074	0.6074	0.1624

Notes. Modification indices of the respecified second-order model. The second to last column contains the standardized modification indices, where the factor variances are fixed to one. The last column presents the completely standardized modification indices, where the factor variances are fixed to one and all other parameters are standardized.