Do Different Bank-Level Securitization Variables Measure The Same Thing? A Confirmatory Factor Analysis

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Abstract

A diverging range of securitization variables has been used in the banking literature to measure banks' securitization activities. This study analyses whether to what extent these variables measure the same dimensions of the securitization process. We consider large U.S. commercial banks during the 2011–2017 period and focus on a set of eleven securitization variables available in the Call Reports and the HMDA LAR database. Confirmatory Factor Analysis (CFA) shows that eight out of eleven securitization variables share a common securitization dimension (referred to as common 'factor'). Two of the three remaining measures are excluded from the analysis in a specification search. The third remaining measure captures the common securitization factor to a lesser extent, resulting in relatively low correlations with the other variables. According to our CFA, each of the eight variables is a reliable measure of the same underlying securitization factor.

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1. Introduction

Securitization allows banks to remove credit risk from their balance sheet by selling pools of loans to secondary market investors (Greenbaum and Thakor, 1987). By requiring less regulatory capital for assets that were moved off the balance sheet, Basel II regulation stimulated banks' securitization activities. At the same time, securitization resulted in a reduction of banks' loan screening and monitoring efforts. This caused a dramatic accumulation of systemic risk in the economy (Mian and Sufi, 2009; Berndt and Gupta, 2009; Keys et al., 2010; Purnanandam, 2011; Maddaloni and Peydró, 2011; Nijskens and Wagner, 2011; Agarwal et al., 2012; Dell'Ariccia et al., 2012; Jiang et al., 2014; Elul, 2016; Beltran et al., 2017; Thornton, 2021). Eventually, this accumulation culminated in the Great Recession that started with the fall of Lehman Brothers in September 2008.

Ever since, studies have investigated the relation between bank-level securitization and bank characteristics such as risk, market power, efficiency, and profitability. The choice of the securitization measure turns out to differ substantially across bank-level studies. This is illustrated in Table 1, which provides a (non-exhaustive) overview of bank-level securitization studies published between 2007 – 2022. We observe that a wide range of bank-level securitization measures has been used in the literature, coming from multiple data sources. This observation raises the question of whether different securitization variables actually measure the same thing. We may expect that different measures capture different dimensions of the securitization process. These dimensions could be related to, for instance, the type transformation used in the securitization process (asset or maturity) and the type of risk transfer (cash or synthetic). Because bank-level securitization measures are typically based on data coming from balance sheets, income statements and annual reports, it is often not a priori clear what dimensions of the securitization process they capture. For researchers, however, this is crucial information in order to make a grounded choice among the available securitization measures.

To the best of our knowledge, the question of whether different securitization variables actually measure the same thing has not yet been addressed in the literature. Our study fills the gap by exploring this issue for large U.S. commercial banks during the 2011 – 2017 period. We focus on a set of securitization measures available in two publicly available databases. We use Confirmatory Factor Analysis (CFA) – a form of Structural Equation Modeling – to analyze whether the correlations among different measures can be explained by one or more common dimensions (referred to as common 'factors'). We first determine the common factors that are shared by the securitization variables. Subsequently, we identify the securitization variables that measure these common factors 'reliably', which according to CFA is the case if the variable shares a sufficiently large part of their variance with the common factors. This approach will make clear to what extent our set of securitization variables measure the same thing.

The two data sources that we use are 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). The former source contains bank-level data, while the latter consists of loan-level data that we aggregate at the bank level. Our final sample includes 750 commercial banks, each with total assets of at least $1 billion, and 3,798 bank-years. In total, we consider eleven securitization measures.

A statistical complication is that only a few very large banks securitize their assets, causing the securitization measures to have high percentages of zero values and relatively low variances. To deal with the possibility of finite-sample bias, we combine CFA with a bootstrap-based bias correction in a robustness check (Dhaene and Rosseel, 2022). Instead of referring to dimensions, we will henceforth use the CFA terminology by speaking about 'factors'.

In contrast to our initial expectations, we find little evidence that different securitization variables measure different dimensions of securitization. That is, we show that eight out of eleven securitization variables strongly correlate with each other, because they share a single common securitization factor. Each of these eight variables reliably measures the securitization factor. Two of the three remaining measures are excluded from the analysis in a specification search. The third remaining measure exhibits relatively low correlations with the other variables, as well as a low reliability with the common factor. We explain the deviating properties of the third variable from the noisy way this variable measures securitization. Throughout, the small-sample bias of the CFA analysis turns out negligible according to the bootstrap analysis. Hence, the use of securitization measures with high percentages of zero values does not hamper our analysis.

The remainder of the study is as follows. Section 2 discusses the most common forms of securitization and provides a review of the literature on popular securitization measures. Section 3 presents the data, the selected securitization measures and sample statistics. Section 4 discusses the modeling approach, while Section 5 describes the specification search for the most appropriate model. The final estimation results are presented in Section 6 together with robustness checks. Lastly, Section 7 draws conclusions and provides recommendations for future research. An online appendix with supplementary material is available.

2. Literature review

This section explains banks' securitization process and reviews the measurement of securitization in the literature.

2.1. Securitization process

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). In particular, a bank or financial institution transfers the rights to cash flows of financial assets or their underlying credit risk to a legally separate and bankruptcy-remote off-balance SPV, which pools the assets and sells securities linked to the asset pools.

Securitization can either be cash (true sale) or synthetic. Cash securitization involves the sale of assets to an SPV, moving them off-balance-sheet from the securitizer. Synthetic securitization uses credit derivatives to transfer the underlying risk of assets to an SPV. In this way, the securitizer retains the assets on its balance sheet, but transfers credit risk. Credit default swaps are the most commonly used credit derivatives in synthetic securitization (see Lancaster et al., 2008). We note that credit derivatives are also used outside of securitization to hedge credit risk.

In practice, there are many different ways to securitize. We discuss the most popular forms: asset-backed securities (ABS), collateralized debt obligations (CDO) and asset-backed commercial paper (ABCP). The first and most popular form of securitization is based on ABS (Gorton and Metrick, 2013). ABS are the product of a cash securitization process and typically include credit-card receivables, mortgages and small business loans as collateral. A second popular form of securitization is based on CDO, which can be cash or synthetic. CDO often use ABS as their asset pools, but can also include other securities, assets or credit derivatives (Schönbucher, 2003; Fabozzi et al., 2006; Gorton and Metrick, 2013). The last form is ABCP securitization. Similar to the previous forms, it involves asset transformations. In addition, it also applies a maturity transformation. That is, limited-purpose, managed ABCP-conduits or Structured Investment Vehicles (SIV) purchase high-quality medium- and long-term ABS and fund themselves with cheap, highly rated, mostly short-term and medium-term commercial paper (Fabozzi et al., 2006; Gorton and Metrick, 2013). ABCP securitization can also be synthetic. We refer to Section A of the appendix for a stylized visualization of the various forms of securitization.

2.2. Securitization measures

We take a second look at Table 1, which provides a (non-exhaustive) overview of bank-level securitization studies published between 2007 – 2022. As observed in the introduction, a diverging range of bank-level securitization measures has been used, coming from different data sources. Table 1 also makes clear that some of the bank-level studies use measures in continuous levels, while others use a binary variable indicating whether the continuous securitization measure has a non-zero value or not.

For the U.S., popular data sources for securitization measures include the Federal Reserve's Reports of Condition and Income (Call Reports), the Securities and Exchange Commission, and the Home Mortgage Disclosure Act's Loan Application Register (HMDA LAR). The latter database provides information at the loan level, which can be aggregated at the bank level.

[Table 1 about here.]

3. Data

The Call Reports contain information on banks' balance sheets, income statements and off-balance-sheet items. We only use the year-end filings, because the quarterly reports contain too many missing items. We confine our analysis to all FDIC-insured commercial banks with a physical location in the U.S.

The HMDA LAR data cover about 90% of all originated residential mortgages in the U.S. (Dell'Ariccia et al., 2012). For each mortgage that a bank issued or refinanced in a particular year, the HMDA LAR information makes clear whether the mortgage has been approved by the bank and accepted by the applicant. For mortgages that have been approved and accepted, it is also reported whether they have been sold by the bank to a Government-Sponsored Enterprise, private party, or private securitizer. A mortgage is tagged as sold to a private securitizer if it is sold to a private party during the year of origination who is expected to securitize the loan.

Our sample starts in 2011, because from that year on the Call Reports include information on the total assets of securitization vehicles and ABCP conduits. The start of the sample in 2011 also avoids potential structural breaks induced by the adoption of the Dodd-Frank Act. Our sample ends in 2017, because from 2018 onward only banks with total assets over $10 billion were obliged to report credit exposure and unused commitments to ABCP conduits. During part of the sample period, only banks with more than $1 billion in total assets were obliged to report information on ABCP securitization. We therefore exclude all banks with total assets under $1 billion. We match the Call Report bank-level data with the mortgage information from the HMDA LAR database aggregated at the bank level. The matching of the two databases is done using the HMDA LAR lender file (known as 'the Avery file', cf. Bhutta et al. (2017)). The resulting sample covers the 2011–2017 period, including 750 unique banks and 3,798 bank-years. For more details on the process of data collection and filtering, we refer to Section B.

3.1. Securitization measures

We obtain eleven securitization measures from the publicly available Call Reports and the HMDA LAR. We denote these measures by $x_1, \ldots, x_{11}$. All measures are binary, indicating whether the underlying continuous securitization measure has a non-zero value or not. Many other studies have also used binary securitization measures, as can be seen from Table 1. As will become clear in Section 4, the use of binary instead of continuous measures results in a better model fit, which explains our choice.

The headers in boldface in Table 2 indicate the type of securitization each measure belongs to. Five measures relate to ABS-CDO securitization. Because ABS and CDO securitization are very much intertwined in our data, these measures relate to both types. Another five measures are associated with ABCP securitization. The measure *Credit Default Swaps Purchased* (labelled x_6) relates to synthetic securitization and is associated with both ABS-CDO and ABCP securitization.

One of the securitization measures comes from the loan-level HMDA LAR database, after aggregation to the bank level (e.g., Loutskina and Strahan, 2009; Purnanandam, 2011; Gilje et al., 2016). In each year, this measure represents the total value of the residential mortgages that the bank issued or refinanced in that year and sold to a private securitizer. We focus on private securitizers, because loans sales to Government-Sponsored Enterprises do not necessarily involve securitization.[1]

As shown by Table 1, several measures in our set of eleven securitization variables have been used in previous U.S. bank-level and bank-holding company studies. As mentioned before, the information offered by the Call Reports and related data sources is not constant over time, which may cause differences in the availability or definition of the securitization measures. The eleven measures that we have selected are available throughout the entire sample period.

[Table 2 about here.]

Three measures suffer from certain measurement issues. For *Small Business Obligations Transferred* (x_1), we do not observe whether the associated obligations have been merely sold or truly securitized. This measure may therefore reflect loan sales instead of securitization, or a combination of both. The problem with *Securitized Residential Mortgages* (x_4) is that it may be subject to measurement imprecision. In the HMDA LAR, a mortgage is tagged as securitized if, in the year of origination, it is sold to a private party who is expected to securitize the loan. Lastly, the measure *Credit Default Swaps Purchased* (x_6) may capture the use of credit default swaps for purposes other than securitization. We will keep these issues in mind for later, when we turn to the interpretation of our estimation results.

[1]Loan sales refer to the sale of (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). Similar to cash securitization, loan sales transfer assets off the balance-sheet. Unlike securitization, however, the loans are directly sold to investors with neither a maturity transformation nor the use of an SPV.

3.2. Sample statistics

For each year and each securitization measure, Table 3 reports the number of banks with a non-zero value. The measures *Securitized Residential Loans*, *Securitized Residential Mortgages* and *Total Assets Securitization Vehicles* are the three securitization variables with the lowest percentages of zero values.

[Table 3 about here.]

[Table 4 about here.]

Table 4 confirms that our eleven binary measures exhibit high percentages of zero values, but also reveals substantial differences in the means and standard deviations across measures. The literature has already noted that securitization is typically only performed by the very large banks, explaining the high percentages of zero values in Table 4 (e.g., Casu et al., 2013). Table 5 shows the sample means and standard deviations of total assets for two groups of banks. The group 'With securitization' contains the banks that have at least one non-zero value for at least one securitization measure in at least one year of the sample (15% of the bank-year observations). The group 'Without securitization' is formed by the remaining banks, who have zero values for all securitization measures during all years of the sample (85% of the bank-year observations). We indeed observe that the first group has a much higher average level of total assets than the second group. Also the dispersion from the mean is much larger for the first group. Substantial differences are also found for the 95% quantile of total assets, which is again much larger for the first group. On the basis of the sample statistics, we decide to drop the measure *Credit Exposure to Other ABCP Conduits* (x_{11}) because of too few non-zero values. This leaves us with ten measures to consider in our remaining analysis.

[Table 5 about here.]

Figure 1 shows the correlation matrix for the remaining ten binary measures, containing mostly moderately positive numbers and some small negative numbers. Pairs of measures with a correlation above 0.5 are *Total Assets ABCP Conduits* (x_7) and *Unused Commitments to Own ABCP Conduits* (x_8), as well as *Total Assets ABCP Conduits* (x_7) and *Credit Exposure to Own ABCP Conduits* (x_9). The measures *Small Business Obligations Transferred* (x_1) and *Securitized Residential Mortgages* (x_4) have particularly low correlations with the other measures and each other. As explained in Section 3.1, these two measures suffer from certain measurement issues. As a result of this, they could be inaccurate measures of securitization, explaining the low correlation with the other measures. Our CFA will come back to this in a more formal way.

[Figure 1 about here.]

4. Latent factor model

Structural Equation Modeling (SEM) is an approach that specifies the relations among observed and unobserved variables (Hoyle, 2012; Brown, 2015). The type of SEM used in this study is Confirmatory Factor Analysis (CFA), which focuses on the estimation of a latent factor model. Latent factor models assume that measures correlate with each other due to the presence of unobserved common factors. In the remainder of this study, we will simply refer to the shorthand 'latent-factor model' or 'CFA'.

4.1. *Confirmatory Factor Analysis*

Our latent-factor model is specified as

$$x = \Lambda\eta + u, \tag{1}$$

where $x = (x_1, \ldots, x_k)'$ is a vector with k observed securitization measures, $\eta = (\eta_1, \eta_2, \ldots, \eta_m)'$ a vector containing m unobserved factors, Λ a $k \times m$ matrix of factor loadings, and $u = (u_1, \ldots, u_k)'$ a k-vector of errors. We assume that $\mathbb{E}(u) = \mathbb{E}(\eta) = \mathbb{E}(u\eta) = 0$. In the classical CFA, it is also assumed that η and u (and thereby x) are multivariate normal.

According to (1), measures that share a latent factor are correlated. More specifically, in terms of covariance matrices, we get

$$\Sigma = \Lambda\Psi\Lambda' + \Theta, \tag{2}$$

where $\Sigma = \mathbb{C}\mathrm{ov}\,(x)$ is the covariance matrix of the measures, $\Psi = \mathbb{C}\mathrm{ov}\,(\eta)$ denotes the covariance matrix of the unobserved common factors, and $\Theta = \mathbb{C}\mathrm{ov}\,(u)$ is the covariance matrix of the errors. We infer that the measures' variance can be decomposed into variance stemming from the latent factors (the common variance or communality) and variance coming from the errors (the unique variance).

We focus on the case of ordered binary measures and assume that a latent, normally distributed response variable x_i^* underlies each observed binary measure x_i ($i = 1, \ldots, k$). Hence, for threshold values τ^i, we assume that

$$x_i = \begin{cases} 1 & \text{if} \quad x_i^* > \tau^i \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Our CFA consists of Equation (1) with x replaced by $x^* = (x_1^*, \ldots, x_k^*)'$, in combination with Equation (3) for each i. In this setting, the covariance matrix Σ in Equation (2) captures the covariances among the underlying normally distributed response variables. It will be referred to as the *tetrachoric* covariance matrix.

4.2. Estimation methods

The classical estimation method for CFA is maximum likelihood (ML), which assumes that measures, unobserved factors, and errors have a multivariate normal distribution. To estimate our CFA model in the presence of binary data, we choose Mean and Variance Adjusted Weighted Least Squares (WLSMV) method of Muthén (1984) as the main estimation method. Several studies have shown that WLSMV exhibits favorable properties with respect to (ordered) categorical, non-normal measures (Beauducel and Herzberg, 2006; Yang-Wallentin et al., 2010; Brown, 2015; Li, 2016).[2] The technical details of this estimation method are provided in the appendix; see Section C.

An important feature of any CFA is that it restricts certain elements of Λ and Θ to be zero for the purpose of identification (Brown, 2015). Suitable restrictions should be based on economic theory or empirical evidence. Another aspect of model identification is the use of marker measures. Marker measures are used to scale the factors, ensuring that the metric of the marker measure is passed on to the latent factor (Brown, 2015).

4.3. Reliability of securitization measures

After WLSMV estimation, we will use the estimated CFA to investigate to what extent the measures reliably measure the common securitization factor(s). For this purpose, we will calculate each measure's communality using the estimated factor loadings. The communality reflects the proportion of a measure's variance that stems from the common factors. In the setting of CFA, measures with high communalities are viewed as reliable measures of the latent factors (Brown, 2015). An unreliable measure shares only a small part of its variance with the common factors, while the remaining part of its variance stems from measurement error or other noise.

5. Specification search

This section discusses the specification search that we performed in order to arrive at the most appropriate latent factor model.

5.1. Prior expectations

Based on the theoretical properties of the measures that we have selected for our empirical analysis, we expect them to share two latent securitization factors. In particular, we anticipate to find

[2] We use the WLSMV implementation as available in the `lavaan` library in R.

different factors for (i) securitization that only transforms assets ('without maturity transformation') and (ii) securitization that transforms both assets and maturities ('with maturity transformation'). We do not expect cash and synthetic securitization to show up as two separate factors, because all but one measures potentially relate to both forms of securitization. Only the measure *Credit Default Swaps Purchased* (x_6) applies solely to synthetic securitization, but may also capture the use of credit swaps for purposes other than securitization. Likewise, we do not expect to find different factors related to the data source (Call Reports vz. HMDA LAR), since the same mortgages underlie both databases.

5.2. *Number of factors*

Instead of fixing the number of factors to the expected value of two, we first investigate the latent factor structure present in the binary securitization measures using exploratory factor analysis (EFA). The main difference with the CFA that we run later is that EFA does not involve error correlations and other theory-based restrictions. Another major difference is that the initial specification of the CFA is adjusted in a data-driven way on the basis of so-called fit statistics. These differences explain why EFA is an 'exploratory' method, while and CFA is used to 'confirm' theory.

The complete EFA estimation results are available in Section D of the appendix. According to these outcomes, the appropriate number of factors is two or three. The estimated factor loadings in both the two- and the three-factor EFA suggest that two of the factors represent securitization with and without maturity transformation. The measure *Small Business Obligations Transferred* (x_1) deserves special attention, because it does not saliently load on a factor in the two-factor EFA, while it gets a factor of its own in the three-factor model. We will keep these preliminary outcomes in mind during the formal stage of our specification search.

5.3. *Model selection*

Based on the EFA outcomes, we start by estimating two distinct two-factor CFAs. In the first two-factor model, we put restrictions on the factor loadings in accordance with the two-factor EFA outcomes reported in Section D of the appendix. Hence, this model allows the measures $x_1, \ldots, x_6$ to load on the first factor and $x_6, \ldots, x_{10}$ on the second, while the other loadings are restricted to zero. Only one measure (*Credit Default Swaps Purchased*, x_6) is allowed to load on both factors, while the remaining measures load on a single factor. The first (second) factor is interpreted as securitization without (with) maturity transformation. We will refer to this as the 'basic' two-factor model. In the second CFA, we proceed as in the basic two-factor model but we discard the measure *Small Business Obligations Transferred* (x_1). In a CFA, multiple measures have to load on a factor (Brown, 2015) to ensure identification. Because x_1 is the only measure in the EFA that loads on a third factor, we exclude this measure from the second CFA. We will refer to the resulting model as the 'reduced' two-factor model. We proceed with both two-factor models and will turn to three-factor models in a later stage.

In both CFAs, we use *Securitized Residential Loans* (x_2) and *Total Assets ABCP Conduits* (x_7) as marker measures for the first and second factor, respectively. We choose these two variables as the markers, because they have been frequently used in the existing literature. For a discussion on markers, see Brown (2015, p. 107).

In each of the two-factor models, we allow the latent securitization factors to correlate with each other, because we expect them to share the aspect of asset transformation. Furthermore, we allow the errors of *Total Assets Securitization Vehicles* (u_5) and *Total Assets ABCP Conduits* (u_7) to correlate, because the two measures seem to be based on a similar way of measuring according to their descriptions in the Call Reports ('method covariance', see Brown (2015)). Likewise, we also allow for correlation between the errors of two pairs of ABCP measures (i.e., u_7 and u_9, and u_8 and u_{10}).

Figure 2 visualizes the two different two-factor models by means of a path diagram. Latent factors are represented by circles, observed variables (x) are in boxes, while errors (u) have no frame. Arrows from a latent factor to an observed variable represent the factor loadings, while the arrows from the observed variables to the errors u indicate the unique variances. The double-headed arrow indicates that the two factors are allowed to be correlated. Similarly, the double-headed arrows between certain error pairs indicate that they are possibly correlate with each other.

[Figure 2 about here.]

As part of our specification search, we follow Brown (2015) and Xia and Yang (2019) and compare the basic and reduced two-factor models in terms of their global and local goodness-of-fit as discussed in Section E of the appendix. We investigate possibilities for further model fine-tuning using global and local fit measures. This step also comprises the estimation of several three-factor models.

On the basis of the specification search, we eventually choose the one-factor model as the final specification. Some explanation is in place here. We abandon both the basic and the reduced two-factor models, because in each of them the correlation between the two unobserved factors is above 0.7. Hence, the two factors show a high degree of similarity, which could indicate poor discriminant validity. Most importantly, the global fit of the one-factor model turns out to be better than that of the two-factor models. We emphasize that the estimation results of the basic and reduced factor models are very similar to those of the one-factor model and would not lead to different final conclusions. We therefore consider it legitimate to choose the most parsimonious CFA. The path diagram for this CFA is shown in Figure 3. Full details of the model selection procedure – including the values of the fit measures and other relevant output – are provided in the appendix; see Section F. This section also discusses the estimation of three-factor models.

[Figure 3 about here.]

6. Estimation results

This section discusses the estimation results for the one-factor model that was the outcome of our specification search.

[Table 6 about here.]

6.1. Factor loadings and error covariances

Table 6 applies to the one-factor model and shows the WLSMV-based estimated loadings, error covariances, thresholds and the factor variance, followed by the communalities.

We present both non-standardized and completely standardized estimation results for this model (Brown, 2015). In a non-standardized solution, factor loadings (Λ), factor covariances (Ψ) and measure error covariances (Θ) are based on the original metrics of the measures and latent factors. In completely standardized solutions, the metrics of both measures and latent factors are standardized as to have mean zero and unit variance.

We do not discuss the values of the estimated thresholds and factor variance, but merely report them for the sake of completeness. Instead, we immediately turn to the more informative estimates.

All securitization measures have significantly positive factor loadings, meaning that common factor makes a significant contribution to the observed interrelationships among the measures. Also the factor variance is significant, showing that the measures share a non-degenerate common factor. Two out of three error covariances are statistically insignificant. Only the error covariance between *Total Assets ABCP Conduits* (u_8) and *Credit Exposure to Own ABCP Conduits* (u_{10}) is significantly positive. Later we will run a robustness check to analyze what happens if our CFA discards the two non-significant error correlations.

6.2. Reliability

The lower part of Table 6 reports the measures' communalities. All but one communalities fall in the range 64% – 92% and are significant at the 1% level. The exception is the communality of the measure *Securitized Residential Mortgages* (x_4), which is statistically significant but with a value of only 12%. According to these results, eight out of nine measures are reliable measures of the non-degenerate latent securitization factor. The low communality for x_4 is in line with the low tetrachoric correlations of this measure with the other ones as observed in the tetrachoric correlation matrix (reported in Section G.3 of the appendix). These low values are consistent with the measurement issue discussed in Section 3.1. That is, measurement error could account for the large error variance of u_4 and the low communality with the common factor.

6.3. Robustness checks

We run several robustness checks, including a sensitivity analysis of the one-factor model, estimation of a hierarchical factor model, and estimation based on Unweighted Mean and Variance Adjusted Weighted Least Squares (ULSMV) instead of WLSMV. These additional analyses confirm the choice of our one-factor model as the final model specification and the robustness of its outcomes. We also run an additional analysis to investigate the issue that the binary securitization measures have small percentages of non-zero values and low variances. To account for any finite-sample bias, we obtain a bootstrap-bias correction (Dhaene and Rosseel, 2022). The bias correction turns out negligible, which provides another confirmation of the robustness of our initial estimation results. All robustness checks are discussed in detail in Section H of the appendix with supplementary material.

7. Conclusions

The diverging range of securitization variables used in the literature raises the question of whether different securitization variables measure different dimensions of the securitization process. We have investigated this question for large U.S. commercial banks during the 2011–2017 period, focusing on a set of securitization variables available in the Call Reports and the HMDA LAR database.

Using Confirmatory Factor Analysis (CFA), we have shown that eight out of eleven securitization variables a share a single common securitization factor. Each of the eight measures turned out to measure the common securitization factor reliably. Two of the three remaining measures are excluded from the analysis in a specification search. The third remaining measure exhibits relatively low correlations with both the common factor and the other variables. We have explained the deviating properties of the third variable from the noisy way it measures securitization.

Our results provide a statistical rationale for using either of the eight variables as a measure of securitization. For researchers using different securitization measures or data sources, we recommend them to routinely perform a CFA and to investigate what their securitization variables actually measure. The outcomes of such an analysis could be used to motivate the choice of securitization measures.

A topic that we leave for future research is the use of latent-factor models that explore the structure of panel data. For instance, we may want to specify a separate CFA equation per time point, allowing at least the intercepts to vary over time (Andersen, 2022). Similarly, for a data set with a sufficiently long time dimension, it might be possible to specify a separate CFA equation for each bank. These approaches did not turn out feasible for our analysis, but it would be interesting to apply them to a richer panel data set of securitization measures.

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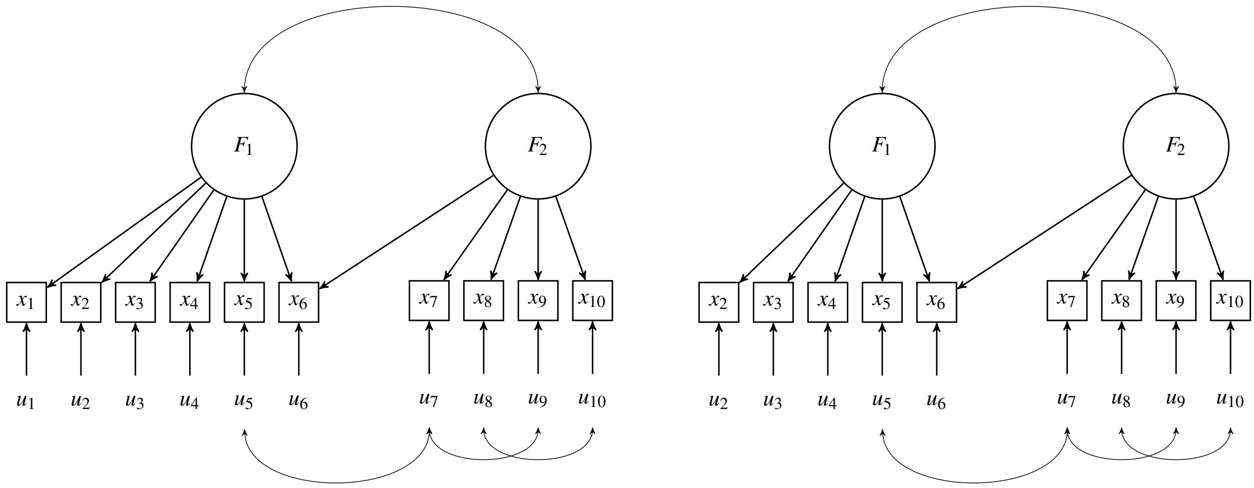
Figure 1: Correlation Matrix

Notes. This figure shows the correlation matrix for the binary securitization proxies in the form of a heat map. All bold-faced correlations are significant at the 5%-level.

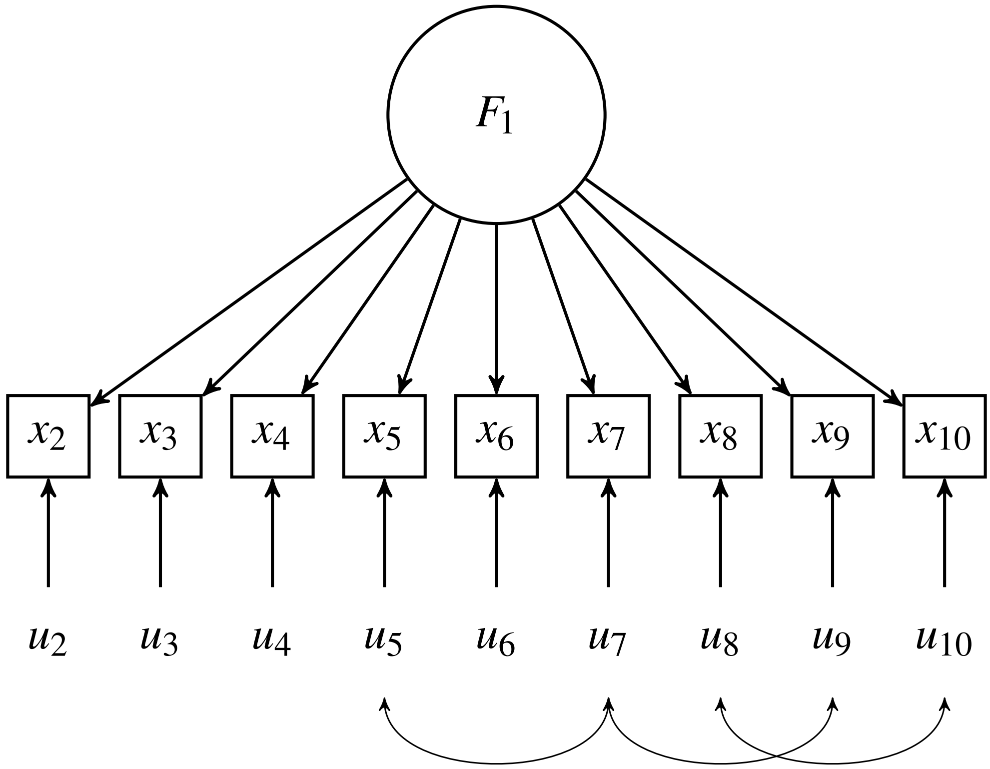
Figure 2: Path Diagrams for Basic and Reduced Two-Factor Models



(a) Two-Factor Model **(b)** Reduced Two Factor Model

Notes. This figure visualizes the basic and reduced two-factor models. The basic two-factor model places the restrictions on the factor loadings in accordance with Table 2. The reduced two-factor model is identical to the two-factor model, except that it does not include the proxy for *Small Business Obligations Transferred* (x_1). Latent factors are visualized by circles, observed variables (x) are in boxes and error terms (u) have no frame. The arrows from the latent factors to the observed variables represent the factor loadings. The double-headed arrow indicates that the two factors are allowed to be correlated, while the double arrows between certain error pairs indicates that they are also allowed to be correlated.

Figure 3: Path Diagram for the One-Factor Model



Notes. This figure visualizes the one-factor model. Latent factors are visualized by circles, observed variables (x) are in boxes and error terms (u) have no frame. The arrows from the latent factors to the observed variables represent the factor loadings, while the double arrows between certain error pairs indicates that they are allowed to be correlated.

Table 1: Overview of Securitization Studies and Their Measures (2007–2022)

Authors	Research Focus	Scope	Data Source(s)	Securitization Measure(s)
Abdelsalam et al. (2021)	Organizational and geographical religiosity as driver of securitization	Islamic World; 2003–2012	ThomsonOne; Orbis; Thomson-Reuters' Refinitiv; IFIS; bank reports	Total asset securitization (level and dummy)
Abdelsalam et al. (2022)	The effect of securitization on bank performance and stability	Islamic World; 2003–2012	Thomson One; Bankscope; Thomson-Reuter's Zaywa; IFIS; bank reports	Total asset securitization (level and dummy)
Acharya et al. (2013)	Structure of risk sharing between ABCP conduits and sponsoring banks	U.S.; 2001–2009	Moody's Investor Service; Bankscope;	Total ABCP outstanding; Total ABCP sponsored with liquidity guarantees; Total ABCP sponsored with credit guarantees
Acharya et al. (2017)	How banks obtained liquidity in response to ABCP-market freezes (BHC)	U.S.; 2007	FFIEC 002; FR Y-9C; Call Reports	Total ABCP outstanding
Altunbas et al. (2022)	The effect of securitization on market power and systemic risk	U.S. and Europe; 2003–2009	DCM Analytics (Dealogic)	Average quarterly total securitization flow
Arif (2020)	The effect of securitization and covered bonds on systemic risk	Europe; 2000–2014	ABS-Alert; Bloomberg; ECBC	ABS issued
Aysun and Hepp (2011)	The effect of securitization on the balance sheet channel of monetary transmission	U.S.; 2001–2009	Call Reports	Principle balance outstanding of assets sold and securitized (level and dummy)
Bayeh et al. (2021)	Securitization, competition and efficiency	U.S.; 2001–2019	Call Reports	Principal balance outstanding of assets sold and securitized (level and dummy)
Beccalli et al. (2015)	The effect of securitization on banks' leverage cyclicality	U.S.; 2001–2010	FR Y-9C (BHC Level)	Principle balance outstanding of assets sold and securitized
Battaglia and Mazzuca (2014)	The impact of securitization on credit and liquidity risk during the crisis	Italy; 2007–2009	Bankscope; Securitization.it	Current and previous cash securitization (dummy)
Cardone-Riportella et al. (2010)	Drivers of securitization	Spain; 2000–2007	Spanish National Securities Market Commission (CNMV)	Total ABS, CDO and ABCP securitization transactions (dummy)
Casu et al. (2013)	The effect of securitization on bank performance	U.S.; 2001–2008	Call Reports	Principle balance outstanding of assets sold and securitized (dummy)
Casu et al. (2011)	The effect of securitization on credit risk taking	U.S.; 2001–2007	FR Y-9C (BHC Level)	Principle balance outstanding of assets sold and securitized
Chen et al. (2019)	The effect of management expertise on securitization policies	U.S.; 2001–2011	FR Y-9C (BHC Level)	Principle balance of loans sold and securitized for different asset categories; Aggregate retained interest
Chen et al. (2017)	The effect of securitization on bank risk	U.S.; 2002–2012	Call Reports	Principle balance outstanding of mortgage and non-mortgage loans sold and securitized
Cheng et al. (2011)	Securitization and asymmetric information	U.S.; 2001–2007	FR Y-9C (BHC Level)	Total securitized assets; Securitization income and servicing fees
Dionne and Harchaoui (2008)	The effect of securitization on bank risk taking	Canada; 1988–1998	Canadian Banking Association	Total securitized assets
Farruggio and Uhde (2015)	Drivers of securitization	Europe; 1997–2010	Moody's; Standard & Poor's; FitchRating	Cumulated annual securitization volume for different asset categories (level and dummy)

Table 1 *(continued)*

Authors	Reseach Focus	Scope	Data Source	Securitization Measure
Gilje et al. (2016)	Bank branching and the expanse of (securitized and non-securitized) mortgage lending following a liquidity shock	U.S.; 1992–2004	Call Reports; HMDA LAR	Growth in sold mortgages loans
Ivanov and Jiang (2020)	The effect of securitization on systemic risk	U.S.; 2004–2016	FR Y-9C (BHC Level)	Principal balance outstanding of assets sold and securitized for different asset categories; Total amount of held-to-maturity and available-for-sale MBS and ABS
Kisin and Manela (2016)	Shadow costs of capital requirements	U.S.; 2002–2012	Moody's Investor Service; Bankscope	Total ABCP outstanding; Total liquidity provisions to ABCP conduits
Kundu (2022)	Design and structure of the CLO market	U.S.; 2002–2021	S&P Leveraged Commentary & CreditFlux's CLO-i Database; Moody's Analytics Structured Finance	Amount of CLO issued; Amount of CLO-assets under management
Lacina et al. (2020)	The effect of securitization on earnings smoothing	U.S.; 2001–2018	FR Y-9C (BHC Level)	Securitization income
Le et al. (2016)	The effect of securitization on bank risk taking	U.S.; 2001–2012	FR Y-9C (BHC Level)	Total securitized assets (level and dummy); Interest retained in securitization; Net charge-offs from securitized assets; Nonperforming loans from securitized assets
Michalak and Uhde (2012)	The effect of securitization on bank stability	Europe; 1997–2007	Moody's, Standard & Poor's; FitchRating	Cumulated volume of cash and synthetic credit risk securitizations with different asset categories
Nijskens and Wagner (2011)	The effect of credit risk transfer on systemic risk	U.S.; 1996–2004	ABS Alert; Call Reports	CLO issued; CDSs traded
Purnanandam (2011)	The effect of originate-to-distribute activity on loan quality	U.S.; 2006–2008	Call Reports;	Residential mortgage loans designated for sale and actually sold;
Ryan et al. (2016)	Securitization and insider trading	U.S.; 2001–2007	FR Y-9C (BHC Level)	Principle balance of assets sold and securitized for different asset categories; Securitization income
Trapp and Weiß (2016)	The effect of securitization on extreme equity returns	U.S.; 2006	SEC 10-K Filings	Loan securitization (dummy)
Uzun and Webb (2007)	The effect of securitization on bank characteristics and capital arbitrage	U.S.; 2001–2005	Call Reports	Principle balance outstanding of assets sold and securitized
Wu et al. (2011)	The effect of securitization on the market perception of banks' risk exposure	U.S; 2002–2007	FR Y-9C (BHC Level)	Total securitized loan balance; Total securitization income
Wengerek et al. (2022)	The effect of securitization on NLP exposure	Europe; 1997–2010	Moody's; Standard & Poor's; FitchRatings	Cumulated volume of true sale securitizations

Notes. This table provides a non-exhaustive list of 2007 — 2021 bank- and bank-holding company (BHC) level studies that use one or more securitization measures.

Table 2: Binary securitization Variables

Name (identifier)	Description of underlying variable	Relevant mnemonic
Proxies for ABS-CDO securitization		
Dummy for Small Business Obligations Transferred (x_1)	Principal balance outstanding of small business loans and leases on personal property, transferred with recourse.	A249
Dummy for Securitized Residential Loans (x_2)	Principal balance outstanding of 1–4 family residential loans sold and securitized with recourse or other seller provided credit enhancements.	B705
Dummy for Securitized Other Assets (x_3)	Principal balance outstanding of other loans sold and securitized with recourse or other seller provided credit enhancements.	∑(B706, B707, B708, B709, B710, B711)
Dummy for Securitized Residential Mortgages (x_4)	(HMDA LAR) Residential loans sold and securitized.	Type of entity purchasing a covered loan from the institution; 5 – private securitizer
Dummy for Total Assets Securitization Vehicles (x_5)	Assets of consolidated variable interest entities that can be used only to settle obligations of the consolidated entities.	∑(J981, J984, J987, J990, J996, J999, K003, K006, K009, K012)
Proxies for ABS-CDO and ABCP securitization		
Dummy for Credit Default Swaps Purchased (x_6)	Notional amount of all credit default swaps on which the bank is the protection purchaser.	C969
Proxies for ABCP securitization		
Dummy for Total Assets ABCP Conduits (x_7)	Assets of consolidated variable-interest entities that can be used only to settle obligations of the consolidated entities.	∑(J982, J985, J988, J991, J997, K001, K004, K007, K010, K013)
Dummy for Unused Commitments to Own ABCP Conduits (x_8)	Usused commitments to provide liquidity to conduit structures sponsored by the bank.	B808
Dummy for Credit Exposure to Own ABCP Conduits (x_9)	Maximum amount of credit exposure arising from credit enhancement provided to conduit structures sponsored by the bank in the form of standby letters of credit, the carrying value of subordinated securities, etc.	B806
Dummy for Unused Commitments to Other ABCP Conduits (x_{10})	Unused commitments to provide liquidity to conduit structures sponsored by others.	B809
Dummy for Credit Exposure to Other ABCP Conduits (x_{11})	Maximum amount of credit exposure arising form credit enhancement provided to conduit structures sponsored by others in the form of standby letters of credit, the carrying value of subordinated securities, etc.	B807

Notes. This table describes this study's choice of securitization variables. All of them are based on data from the Call Reports, unless the HMDA LAR is mentioned explicitly. All proxies are binary, indicating whether the value of the continuous proxy is non-zero (value 1) or not (value 0).

Table 3: Number of Banks Per Measure

	2011	2012	2013	2014	2015	2016	2017
Total number of banks	491	512	517	535	557	586	600
Small Bus. Obl. Transf.	5	5	4	4	4	4	5
Sec. Residential Loans	27	29	25	28	32	34	34
Sec. Other Assets	18	20	16	19	21	22	20
Sec. Residential Mortgages	28	32	31	33	32	27	19
TA Sec. Vehicles	27	28	27	26	23	20	18
CDSs Purchased	17	19	18	16	18	18	16
TA ABCP Conduits	7	5	4	3	3	2	2
Un. Com. Own ABCP Conduits	6	7	5	4	4	4	4
Credit Exp. Own ABCP Conduits	4	4	4	4	3	3	3
Un. Com. Other ABCP Conduits	10	8	6	4	4	4	4
Credit Exp. Other ABCP Conduits	1	0	0	0	0	0	0

Notes. For each year and each measure, this table shows the number of banks that have a non-zero value for the measure in that year.

Table 4: Sample Statistics for the Binary Securitization Proxies

	Mean	Std. dev.
Small Bus. Obl. Transf.	0.0082	0.0900
Sec. Residential Loans	0.0550	0.2281
Sec. Other Assets	0.0358	0.1858
Sec. Residential Mortgages	0.0532	0.2244
TA Sec. Vehicles	0.0445	0.2062
CDSs Purchased	0.0321	0.1763
TA ABCP Conduits	0.0068	0.0825
Un. Com. Own ABCP Conduits	0.0090	0.0942
Credit Exp. Own ABCP Conduits	0.0066	0.0809
Un. Com. Other ABCP Conduits	0.0105	0.1021
Credit Exp. Other ABCP Conduits	0.0003	0.0162

Notes. This table shows sample means and standard deviations for the securitization proxies.

Table 5: Sample Statistics Total Assets for Banks With and Without Securitization

	With sec.	Without sec.
Mean	133,497,108	4,775,076
Std. dev.	343,820,599	13,304,739
5% Quantile	1,250,293	1,051,547
95% Quantile	423,346,199	15,971,996

Notes. This table shows sample means, standard deviations and 5% and 95% quantiles of total assets in thousands of U.S. $ for two groups of banks. The group 'With sec.' contains the banks that have at least one non-zero value for at at least one securitization proxy in at least one year of the sample (15% of the bank-year observations). The group 'Without sec.' is formed by the remaining banks, which are those banks that have only zero values for the securitization proxies during all years of the sample (85% of the bank-year observations).

Table 6: Estimation Results: One-Factor Model (WLSMV)

		Estimates	SD	p-value	Estimates (compl. std.)
Factor loadings					
F_1	Sec. Residential Loans	1.0000	0.0000	0.0000	0.8021
	Sec. Other Assets	1.0584	0.0322	0.0000	0.8489
	Sec. Residential Mortgages	0.4297	0.0695	0.0000	0.3446
	TA Sec. Vehicles	1.0922	0.0338	0.0000	0.8761
	CDSs Purchased	1.1100	0.0302	0.0000	0.8903
	TA ABCP Conduits	1.1988	0.0440	0.0000	0.9616
	Un. Com. Own ABCP Conduits	1.1711	0.0471	0.0000	0.9393
	Credit Exp. Own ABCP Conduits	1.0646	0.0633	0.0000	0.8539
	Un. Com. Other ABCP Conduits	1.0960	0.0461	0.0000	0.8791
Error covariances					
Un. Com. Own ABCP Conduits	Un. Com. Other ABCP Conduits	-0.0661	0.0461	0.1521	-0.4041
TA Sec. Vehicles	TA ABCP Conduits	0.0670	0.0456	0.1414	0.5062
TA ABCP Conduits	Credit Exp. Own ABCP Conduits	0.1204	0.0448	0.0071	0.8428
Thresholds					
Sec. Residential Loans		1.5979	0.0333	0.0000	
Sec. Other Assets		1.8015	0.0383	0.0000	
Sec. Residential Mortgages		1.6147	0.0336	0.0000	
TA Sec. Vehicles		1.7007	0.0356	0.0000	
CDSs Purchased		1.8505	0.0397	0.0000	
TA ABCP Conduits		2.4653	0.0700	0.0000	
Un. Com. Own ABCP Conduits		2.3676	0.0632	0.0000	
Credit Exp. Own ABCP Conduits		2.4793	0.0711	0.0000	
Un. Com. Other ABCP Conduits		2.3068	0.0594	0.0000	
Factor variance					
F_1		0.6433	0.0365	0.0000	
Communalities					
Sec. Residential Loans		0.6433	0.0365	0.0000	
Sec. Other Assets		0.7207	0.0369	0.0000	
Sec. Residential Mortgages		0.1188	0.0373	0.0014	
TA Sec. Vehicles		0.7675	0.0322	0.0000	
CDSs Purchased		0.7926	0.0316	0.0000	
TA ABCP Conduits		0.9246	0.0567	0.0000	
Un. Com. Own ABCP Conduits		0.8823	0.0597	0.0000	
Credit Exp. Own ABCP Conduits		0.7291	0.0903	0.0000	
Un. Com. Other ABCP Conduits		0.7728	0.0561	0.0000	

Notes. For the factor loadings, error covariances, thresholds, factor variance and communalities, this table shows their estimated values, standard deviations (SD) and p-values. The last column contains the completely standardized values of the estimated loadings and error covariances. For the remaining estimation output, completely standardized estimates are not informative and therefore not reported. The communalities are expressed as a fraction, representing the fraction of the proxy's variance explained by the common factor.