Transparency as a Remedy for Agency Problems in Securitization? The Case of ECB's Loan-Level Reporting Initiative.[⋆]

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Abstract

Poor transparency of asset-backed securities (ABS) exacerbated the latest subprime lending crisis. In response, the European Central Bank introduced the ABS loan-level reporting initiative, obliging originators to disclose quarterly loan-by-loan information. However, does this increase in transparency alleviate the agency problems inherent in securitization? To answer this question, we examine a novel dataset of 107 ABS pools that are backed by more than 2.8 million loans for small and medium-sized enterprises from the first securitization repository in Europe. The results show that the increase in transparency indeed has valuable effects for investors, inducing originators to improve pool performance and diversification for existing as well as newly issued ABS. These effects persist

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for a large set of control variables and a broad variety of robustness tests.

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1. Introduction

Securitization markets typically exhibited large growth rates up to the latest subprime lending crisis. For example, the total outstanding securitization volume in Europe, the focus area of our study, amounted to around USD 139 billion in 1999 and peaked in 2009 at USD 3.1 trillion (SIFMA, 2019). Securitization helped banks diversify their credit risk and funding sources and promised optimal risk allocation in the credit market, as well as greater overall financial stability. However, the crisis damaged the positive image of asset-backed securities (ABS), revealing severe agency conflicts between originators and investors (Shin, 2009). Investors lacked transparency and access to loan-level information to conduct risk assessments of securitization pools, and had thus to rely heavily on rating agencies. Further, even Moody's only requested loan-level data from issuers as late as 2007 (Pagano and Volpin, 2012), that is, rating agencies deliberately neglected indicators with considerable predictive power (Ashcraft et al., 2010). Additionally, they failed to regularly re-estimate their models (Griffin and Tang, 2012). Both these shortcomings led to rating agencies failing to downgrade ABS ratings until the second half of 2007 (IMF, 2008).

Against this background, opacity was a key driver of the latest subprime lending crisis, and of the ensuing decline of the securitization market (e.g., IMF, 2008). In fact, the volume of outstanding securitizations in Europe almost halved in 2016 compared to 2009 (SIFMA, 2019). To restore overall trust in securitization markets after this decline, market participants called for greater transparency. After a supportive consultation, the European Central Bank (ECB) reacted by launching the ABS loan-level reporting initiative in 2009, which obliges originators to disclose quarterly loan-by-loan information on ABS for the latter to be accepted as collateral in Eurosystem credit operations.[1] As the securitized loans originated after the quarter in which a bank had adopted

[1] The valuable role of loan-level data was also emphasized for the U.S., where the Dodd-Frank Act requires "issuers of asset-backed securities [...] to disclose asset-level or loan-level data, if such data are necessary for investors to independently perform due diligence" (Dodd-Frank Wall Street Reform and Consumer Protection Act, Section 942 [b]).

the new reporting standards are of better quality than other loans securitized by the same bank, the ECB's requirement has positive effects on originator securitization behavior (Ertan et al., 2017).

However, loan pools, as opposed to single loans, are "sold" to ABS investors. Therefore, changes in pool rather than loan quality matter when assessing the impact of a loan-level reporting initiative. Apart from the quality of single loans, pool quality also depends on the composition of the pool, notably its diversification. Additionally, an analysis at the pool level is required to accurately capture its dynamics as many observed ABS pools are not static over time. This entails the introduction of new loans, as well as the exclusion of loans from the already-securitized asset pool over time. For example, there are around 10% new loans in an ABS pool on average in every reporting quarter in our sample. Furthermore, different from the U.S. originate-to-distribute model, in the European market, many loans are securitized considerably after their origination (close to two years on average in our sample). Accordingly, the selection process of loans to be securitized in an ABS pool is of greater relevance for ABS portfolio risk than the lending decisions for single loans.

We investigate whether the ECB's loan-level reporting initiative has had positive effects on pool quality, that is, whether transparent pools perform better[2] and are more diversified than non-transparent ones. Since information asymmetries are of particular importance for small and medium-sized enterprises (SMEs) (Albertazzi et al., 2017), we analyze 107 ABS backed by 2,840,280 SME loans. These data, collected by the European DataWarehouse (ED), the first and only central repository of all loan-level information under the ECB's loan-level reporting initiative, are supplemented by several specific bank characteristics. Using fractional response regression models, we examine five measures of pool performance, as well as four concentration-risk measures. In short, the loan-level reporting initiative works well. Transparent pools exhibit on average lower loss and default rates, lower rates of delinquent amounts and of delin-

[2] We identify better pool performance as lower realized risk, such as loss or default rates.

quent loans, as well as loans with fewer days in delinquency. Additionally, they are more diversified with respect to single-name credit risk, business types, and industries.

The remainder of this paper is organized as follows. Section 2 reviews the related literature and analyzes the status quo of the European securitization market. Section 3 introduces our data sources and sample selection procedure. Section 4 presents the variables and empirical strategy. In Section 5, we discuss the main findings. In Section 6, we examine several competing explanations for our results. Section 7 concludes the paper. The online appendix contains additional information and tables.

2. Literature review and hypotheses development

2.1. Agency conflicts in securitization

Securitization by its very nature comprises agency conflicts, and involved parties thus dedicate significant attention to limiting adverse incentives. This may lead to adverse selection and moral hazard due to information asymmetries between the originator, that is, the bank that initially grants and securitizes loans, and the investors buying ABS tranches. Banks first determine their *screening effort* when originating loans. Second, they choose their *monitoring effort* during the loan repayment term. Third, by selecting loans, they decide about the *pool composition* and therefore pool risk. The literature covers a multitude of theoretical and empirical considerations and results. However, a thorough discussion of this literature stream is beyond the scope of the present paper. For example, there is a broad literature stream on securitizations backed by mortgage loans, which points to agency conflicts by providing evidence for declining bank screening effort (e.g., Keys et al., 2010, 2012).

Nevertheless, our work contributes to the literature on securitizations backed by corporate loans. Bord and Santos (2015) reveal that banks relax lending standards when securitizing loans directly after their origination, which subsequently perform worse. Conversely, Benmelech et al. (2012) mostly find that securitized loans do not perform worse than comparable unsecuritized ones. However, after securitizing a loan, a bank's incentive to conscientiously monitor borrowers tends to decrease, as loan default risk shifts to ABS investors (Wang and Xia, 2014; Kara et al., 2018).

Further implications for the agency problems between investors and originators arise from tranching, which is a common feature of securitization. There are two main dimensions affecting tranche credit risk and pricing. On the one hand, the stand-alone risk of underlying loans is a main driver of portfolio credit risk. On the other hand, the portfolio loss distribution and the resulting tail risk are driven by the default correlation between the underlying assets. By diversification, originators construct low-risk senior tranches, which are usually AAA-rated and almost completely information insensitive (DeMarzo, 2005; Hanson and Sunderam, 2013). From the perspective of social welfare, this alleviates agency problems between originators and investors, as the impact of banks' information advantages diminishes (e.g., DeMarzo, 2005). The low credit risk of AAA-rated tranches implies low incentives for investors to develop expensive expertise in portfolio risk analysis, resulting in a heavy reliance on the risk assessment of a few rating agencies (Hanson and Sunderam, 2013).

There are several instruments counteracting asymmetric information and the resulting agency issues. For example, regulatory requirements and credit enhancements both influence tranche credit risk (e.g., Pagés, 2013). However, transparency via disclosed information is addressed only marginally in the securitization market literature as a remedy. Guo and Wu (2014) prove theoretically that the information-disclosure requirements in securitization markets complement risk-retention regulation. According to their dynamic model with asymmetric information between an originator and a continuum of investors, both the risk-retention and information-disclosure regulations are effective in reducing the negative impacts of investors' informational deficits. Pagano and Volpin (2012) further propose a theoretical model dealing with the impact of transparency on securitization markets, arguing that opacity impedes trading in the secondary market due to adverse selection. Their model offers support for the current efforts of increasing regulatory disclosure standards in securitization markets.[3] Similarly, Chemla and Hennessy (2014) argue that originators have low incentives to exert costly efforts for producing high-quality ABS if investors are unable to observe the true ABS quality. In their theoretical model, investors can receive informative signals under transparency, whereas signaling is not possible under opacity. Ertan et al. (2017) examine empirically the impact of the ECB's loan-level initiative and show that securitized loans originated after the bank adopted the ABS reporting requirement are of better quality. However, there is no unanimous agreement that transparency is indeed beneficial to the banking sector; in some settings it may even worsen the situation (e.g., Goldstein and Yang, 2019).

2.2. Securitization in Europe and the role of the ECB

The International Monetary Fund pinpointed the lack of transparency as a cause of the liquidity drying out in securitization markets during the subprime lending crisis (IMF, 2008). Concurrently, mistrust between banks halted interbank lending and retained securitizations have quickly emerged to represent a large part of outstanding ABS issuances (see Figure A.1 in the online appendix). Subsequently, the ECB increased the attractiveness of ABS as collateral by several measures. First, the ECB reduced the rating threshold from AAA in 2010 to A- in 2011 and to BBB- in 2012. Second, the ECB lowered the "haircut" from 16% on ABS rated between AAA- and A- in 2011 to 10% in 2013. Finally, the ECB started the asset-backed securities purchase program (ABSPP) in November 2014, purchasing securitizations in the primary and secondary market to inject further liquidity into the banking system and stimulate the issuance of new ABS. As of July 2018, the ECB's ABS holdings amounted to around EUR 27 billion (ECB, 2020a), which represents around 1.8% of total

[3] Freixas and Laux (2012) emphasizes it is important to distinguish between disclosure and transparency, since the former refers only to providing information, whereas the latter means the information actually reaches market participants. However, due to the effective information provision of the ECB's loan-level reporting initiative, we do not need to differentiate between disclosure and transparency in our analysis.

outstanding ABS in Europe (SIFMA, 2019).

Accepting securitizations as collateral in monetary policy operations, as well as purchasing them as a result of ABSPP, requires sound ABS risk assessments by central banks. However, the ECB stated that “assessments of asset-backed securities have been hampered by the lack of standardized, timely and accurate information on single loan exposures” (ECB, 2020b). In ABS prospectuses and investor reports, originators only provide aggregated summary statistics of the underlying loan portfolio (Pagano and Volpin, 2012). Unsurprisingly, a public consultation by the ECB, that run from December 2009 until February 2010, revealed broad support for a loan-by-loan disclosure requirement for ABS (see Figure A.2 in the online appendix for the timeline). Therefore, the ECB announced the establishment of the ABS loan-level reporting initiative for residential mortgage-backed securities in December 2010 and for ABS backed by SME loans in April 2011 (ECB, 2011).

In July 2012, ED was established, financed by the European securitization industry. It collects all loan-level information on behalf of the ECB, being the first repository providing granular and standardized information on ABS in Europe, thus enabling extensive comparability across originators. Additionally, it performs data-quality checks for the submitted data (e.g., examining significant deviations in key information compared to previous reports). As of January 2013, originators pledging ABS backed by residential mortgages or by SME loans as collateral for repo agreements with the ECB are obliged to report the required ABS information to ED. Thereafter, disclosure requirements for other ABS classes (e.g., commercial mortgage-backed securities and ABS backed by consumer loans) followed gradually. The novel reporting requirement applies to existing, as well as newly issued ABS. As of January 2020, ED collected loan-level information on around 1,400 ABS deals across Europe (ED, 2020).

2.3. Expected impact of transparency on European securitizations

Increased transparency in general and availability of loan-level information in particular have important implications. *Investors* can perform more comprehensive portfolio risk analyses and use the results to exert a stronger market discipline. *Banks*, as originators, anticipate these and are thereby incentivized to securitize better-performing and more diversified ABS pools as quality signals or to gain reputation in the securitization market (Albertazzi et al., 2015). Overall, we hypothesize that transparent ABS pools, compared to pools that need not yet meet the new rules, perform better and are more diversified.

3. Data sources and sample selection

3.1. Pool Sample

We obtained our main sample, the so-called *Pool Sample*, from ED. It comprises granular information on European ABS pools. Our focus is on ABS backed by SME loans because these loans seem to be particularly affected by information asymmetries, as they are not usually monitored by capital markets (Albertazzi et al., 2017). Furthermore, SMEs are considered an important pillar of EU's economy. On average, more than 80% of all newly issued European ABS backed by loans to SMEs were reported to ED from 2011 to 2017 (SIFMA, 2019). Therefore, a potential bias in the dataset, may result from differences in bank liquidity needs, but should only matter marginally.

ED requires from originators a quarterly reporting of 48 mandatory and 65 optional variables at the loan level, as well as 15 mandatory and 11 optional variables at the tranche level for ABS backed by SME loans. Loan-level data cover six categories of variables: identifiers, obligor information, loan characteristics, interest rate details, financials, and performance measures. Reporting at the tranche level comprises credit enhancements, payment structure, and performance measures. We utilize information from both levels, but mainly focus on mandatory variables because, on average, around 99% of the mandatory and 21% of the optional fields are reported in our sample.

The sample covers the reporting period from 2012 until 2017. To create loan- and tranche-level samples, we conduct separate sample selection procedures at the loan and tranche levels, respectively. At the loan level, we start with 32,026,829 observations (see Table A.1 in the online appendix). First, we delete observations if variables are missing or are implausible and if the originating bank cannot be identified unambiguously. Second, we drop all loan-level observations for which the corresponding tranche-level information is not available. At the tranche level, we begin with 9,969 observations (see Table A.2 in the online appendix). Again, we exclude observations if variables are missing or implausible. We also exclude all tranche-level observations for which the corresponding loan-level information is not available.

Next, we aggregate loan- and tranche-quarter information to create a pool-level database that contains loan and tranche characteristics for each pool-quarter observation. Loan- and tranche-level information are aggregated by using weighted averages. Weighting is based primarily on the current loan or tranche balance to reflect relative loan or tranche size in the portfolio.[4]

As a final step, we adjust our pool-level sample. For voluntary monthly reporting, we use the last observation in a quarter and ignore the previous observations from the same quarter to ensure that securitization pools from monthly reporting originators are not overweighed in our analysis.[5] Using the last observation is motivated by the fact that most quarterly reporting banks report shortly before the end of the respective quarter. Initially starting from 1,405 pool-quarter observations, our final *Pool Sample* comprises 1,072 pool-quarter observations, including 12,311,195 loan-quarter observations for 2,840,280 unique SME loans to 1,213,821 borrowers, collected in 3,847 tranche-quarter observations for 380 ABS tranches and 107 ABS pools from Belgium, France, Germany, Italy, the Netherlands, Portugal, and Spain. These countries represent most Eurozone countries active in SME loan securitization. In Table A.3 in the online appendix, we depict the final *Pool Sample*'s distribution

[4] For loan default or delinquency, the originators in our sample reduce the current loan balance by the default or delinquent amount. We reverse this adjustment by adding the default or delinquent amount to the current loan balance.

[5] As robustness check, we control for *Monthly Reporting*, defined as an indicator variable equal to one if a bank reports on a monthly basis, and zero otherwise. The outcome is the same as in our baseline regression (see Table A.33 in the online appendix).

by the reporting year and country.

As we retain around 38% of the loan- and tranche-level observations, we compare the different characteristics of the final sample with those of the original sample to ensure the *Pool Sample* is representative. As a first step, we conduct a two-sample t-test for the differences in the means and a two-sided Wilcoxon rank sum test for the differences in the medians of the variables used in our first baseline regression (see Table A.4 in the online appendix). Remarkably, the differences between the means and medians of our final and original samples are negligible numerically, although we observe statistical significance. As a second step, we examine the number of pools, banks, loans, and SMEs over time in our final and original samples (see Table A.5 in the online appendix). Overall, we do not systematically exclude specific observations.

3.2. Pool/Bank Sample

We utilize our final *Pool Sample* as a starting point for creating the *Pool/Bank Sample* by adding characteristics of the originating bank and incorporating the loan probabilities of default (PDs).

First, we complement the *Pool Sample* with annual characteristics of originating banks, collected from Fitch Connect. This information is only available for 62 ABS pools. Second, we estimate a PD for each individual loan observation, based on our loan-level database. As we apply pool fixed effects (FE) when estimating PDs, we drop pool observations without defaults because, for them, loan default is perfectly predictable. In total, we exclude 492 pool-quarter observations.

Finally, our *Pool/Bank Sample* comprises 580 pool-quarter observations, namely 1,075,039 unique SME loans to 640,015 borrowers, securitized in 219 ABS tranches and 62 ABS pools.

4. Variable construction and empirical strategy

4.1. General remarks

This section defines the variables used in the empirical analysis (see Table 1). The summary statistics in Table 2 refer to the *Pool Sample* (upper panel) and the *Pool/Bank Sample* (bottom panel). Table A.6 in the online appendix shows the variables' pairwise correlations for both samples. Multicollinearity is neither an issue in the *Pool Sample* (average variance inflation factors of 1.53 and all values below 2.05), nor in the *Pool/Bank Sample* (1.49 and 1.93, respectively).

Table 1: Variable definitions

Variable	Description	Data source
Pool performance measures		
Loss Rate	Weighted average of every loan's loss rate, calculated as the default amount divided by the current loan balance.	ED, own calc.
Default Rate	Weighted average default indicator variable (default indicator equals one if the borrower defaulted on the loan, and zero otherwise).	ED, own calc.
Rate of Delinquent Amounts	Weighted average of every loan's delinquent amount, including principal and interest arrears, divided by the current loan balance.	ED, own calc.
Rate of Delinquent Loans	Weighted average delinquent indicator variable (delinquent indicator equals one if the borrower is in arrears, either with respect to principal or interest payments, and zero otherwise).	ED, own calc.
Number of Days in Delinquency	Weighted average of the natural logarithm of every loan's days in delinquency.	ED, own calc.
Pool diversification measures		
$\bar{I}$ Index	Single-name credit concentration risk index proposed by Uberti and Figini (2010).	ED, own calc.
Business Type HHI	Scaled inverse of the HHI relating to borrowers' legal form (e.g., public company, limited company, partnership, individual, other).	ED, own calc.

Table 1: Definitions of our variables (continued)

Variable	Description	Data source
Industry HHI	Scaled inverse of the HHI relating to borrowers' two-digit NACE industry code.	ED, own calc.
Geographic HHI	Scaled inverse of the HHI relating to borrowers' one-digit postcode.	ED, own calc.
Transparency characteristic		
Transparent Pool	An indicator variable equal to one if a pool's issue date is chronologically after the loan-level reporting requirement for SME loan securitizations was announced in April 2011, and zero otherwise. After a maximum period of two years subsequent to its first reporting quarter, every pool is classified as transparent.	ED, own calc.
Loan-level characteristics		
Interest Rate	Weighted average loan interest rate (%).	ED, own calc.
Collateralization	Weighted average collateral indicator variable (collateral indicator equals one if the loan is collateralized, and zero otherwise).	ED, own calc.
Loan Years to Maturity	Weighted average of the natural logarithm of the remaining loan years to maturity.	ED, own calc.
Securitized Loan Ratio	Weighted average ratio of the loan balance outstanding at the time of securitization to the original loan amount.	ED, own calc.
Lending Relationship	Weighted average lending relationship indicator variable (lending relationship indicator equals one if a borrower has borrowed at least twice from the same bank, and zero otherwise).	ED, own calc.
Tranche- and pool-level characteristics		
Tranche Years to Maturity	Weighted average of the natural logarithm of the tranches' remaining years to maturity.	ED, own calc.
Number of Tranches	Total number of tranches in a securitization transaction.	ED, own calc.

Table 1: Definitions of our variables (continued)

Variable	Description	Data source
Pool Size	Natural logarithm of the sum of loan current balances in a securitization pool.	ED, own calc.
Information Collection	Natural logarithm of the ratio of non-missing variables reported to ED.	ED, own calc.
Banking Sector Condition	Natural logarithm of the number of ABS pools that were issued in the same year and country.	ED, own calc.
Pool Dynamics	Share of new loans added to already-securitized asset pools compared to the previous reporting quarter.	ED, own calc.
Bank characteristics		
Bank Size	Natural logarithm of bank total assets (in million).	Fitch Connect
Loan Ratio	Sum of net loans divided by bank total assets.	Fitch Connect
NPL Ratio	Ratio of non-performing loans volume to gross loans volume.	Fitch Connect

All variables refer to the pool or bank level. The aggregation procedure at the pool level is explained in more detail in Section 3.1. All weights are based on the current loan or tranche balance.

4.2. Identification strategy for transparent pools

Our main exogenous variable is *Transparent Pool*, which characterizes a pool satisfying the loan-level reporting requirement outlined above. Given that it applies to both existing and newly issued ABS, we are able to analyze the differences between securitization pools under the pre-transparency and the transparency regimes, respectively. We define *Transparent Pool* as an indicator variable reflecting whether a pool is affected by the new transparency regime.

We determine this indicator variable in two subsequent steps. First, we define pools under the transparency regime as those issued after the loan-level reporting requirement was announced for SME loan securitizations in April 2011. From then onwards, banks were able to adjust their securitization behaviors to the novel rules for the first time. They more or less had to do so, because the

Table 2: Summary statistics for the *Pool Sample* and *Pool/Bank Sample*

Variable	*Pool Sample* N	Mean	SD	p10	p50	p90
Pool performance measures						
Loss Rate	1,072	0.04	0.07	0.00	0.01	0.13
Default Rate	1,072	0.14	0.21	0.00	0.07	0.36
Rate of Delinquent Amounts	1,072	0.02	0.03	0.00	0.01	0.06
Rate of Delinquent Loans	1,072	0.16	0.14	0.00	0.14	0.35
Number of Days in Delinquency	1,072	0.60	0.61	0.00	0.45	1.49
Transparency characteristic						
Transparent Pool	1,072	0.75	0.43	0.00	1.00	1.00
Loan-level characteristics						
Interest Rate (%)	1,072	2.63	0.90	1.52	2.55	3.91
Collateralization	1,072	0.85	0.22	0.54	0.95	1.00
Loan Years to Maturity	1,072	1.89	0.43	1.45	1.98	2.27
Securitized Loan Ratio	1,072	0.82	0.14	0.64	0.84	0.94
Lending Relationship	1,072	0.35	0.27	0.08	0.26	0.78
Tranche- and pool-level characteristics						
Tranche Years to Maturity	1,072	3.41	0.58	2.53	3.57	3.88
Number of Tranches	1,072	3.60	3.79	1.00	3.00	6.00
Pool Size	1,072	19.96	1.44	18.11	19.94	21.88
Information Collection	1,072	4.32	0.11	4.26	4.27	4.57
Banking Sector Condition	1,072	1.63	0.70	0.70	1.61	2.71
Pool Dynamics	1,072	0.10	0.24	0.00	0.00	0.28

Variable	*Pool/Bank Sample* N	Mean	SD	p10	p50	p90
Pool diversification measures						
$\bar{I}$ Index	580	0.98	0.03	0.96	0.99	1.00
Business Type HHI	580	0.42	0.26	0.01	0.46	0.74
Geographic HHI	580	0.65	0.23	0.26	0.72	0.87
Industry HHI	580	0.92	0.07	0.88	0.93	0.96
Transparency characteristic						
Transparent Pool	580	0.66	0.47	0.00	1.00	1.00
Tranche- and pool-level characteristics						
Tranche Years to Maturity	580	3.55	0.43	3.22	3.64	3.87
Pool Size	580	20.24	1.41	18.50	20.09	22.35
Information Collection	580	4.27	0.09	4.25	4.27	4.45
Pool Dynamics	580	0.05	0.16	0.00	0.00	0.12
Bank characteristics						
Bank Size	580	11.32	1.64	9.15	11.02	13.44
Loan Ratio	580	0.63	0.13	0.51	0.63	0.79
NPL Ratio	580	0.11	0.09	0.03	0.08	0.25

This table reports the descriptive statistics for the variables used in our analysis. Variables are described in Table 1. N refers to the number of observations. SD means standard deviation. p10, p50, and p90 represent the tenth, fiftieth, and the ninetieth percentile.

ECB published its decision requiring loan-level reporting for ABS backed by SME loans within the next 18 months (ECB, 2011). Second, we account for the fact that most ABS pools in our sample are not static, that is, pool composition changes regularly over time. Thus, a pool need not be either transparent or non-transparent over its entire lifetime. To adjust the static definition of *Transparent Pool*, we allow pools to be classified as non-transparent for a maximum of two years after first reporting a quarter to ED. We choose two years to incorporate the time lag banks potentially need to adjust the composition of already existing pools in April 2011. In Section 5.1, we alter this assumption to check for robustness. The mean value of *Transparent Pool* is 0.75, meaning that 75% of observations refer to ABS pools under the transparency regime.

4.3. Pool performance measures

We use five endogenous variables to measure the impact of transparency on pool performance: *Loss Rate* (1), *Default Rate* (2), *Rate of Delinquent Amounts* (3), *Rate of Delinquent Loans* (4), and *Number of Days in Delinquency* (5).

Loss Rate refers to the weighted mean of each loan's loss rate, calculated as the ratio of the default amount to the current loan balance. *Default Rate* is computed as the weighted average default loan-level indicator. This default indicator equals one if the borrower defaulted on the loan, and zero otherwise. In the *Pool Sample*, the mean of *Loss Rate* is 4% and that of *Default Rate* is 14%, indicating substantial recovery rates. Similarly, *Rate of Delinquent Amounts* represents the weighted mean of each loan's delinquent amount, including the principal and interest arrears, divided by the current loan balance. *Rate of Delinquent Loans* refers to the weighted average delinquency loan-level indicator and equals one if the borrower is in arrears with respect to the principal or interest payments, and zero otherwise. *Number of Days in Delinquency* represents the weighted mean of the natural logarithm of the number of days for which the borrower is in arrears, concerning principal or interest payments as well. In our sample, *Rate of Delinquent Amounts* accounts for 2% and *Rate* *of Delinquent Loans* for 16% on average. The mean of *Number of Days in Delinquency* is 0.6, which translates to around 2.6 days.

4.4. Pool diversification measures

In addition to pool performance, we analyze the impact of transparency on the diversification of securitization pools using four measures. First, we calculate single-name credit concentration risk. Uberti and Figini (2010) propose the following index:

$$\bar{I}\ Index = \frac{\sum_{l=1}^{n}(x_l)^2 PD_l}{max\{PD_l\}}. \tag{1}$$

The portfolio share of loan l is x_l, PD_l is its PD, and n the total number of loans in the portfolio. The index weights the squared loan shares in the portfolio with the respective PDs, that is, it considers not only the size distribution of loans, but also incorporates the linkages between single-name concentration and individual default risk. We estimate PDs based on our loan-level database by applying a probit model and utilizing a default indicator as endogenous variable. In the probit model, our exogenous variables refer to several borrower and loan characteristics and we apply various FE. The results are reported in Table A.7 in the online appendix.

For simplicity, we will refer to $\bar{I}$ *Index*, although, strictly speaking, we use an adjusted $\bar{I}$ Index:[6]

$$\bar{I}\ Index^{Adjusted} = 1 - (\bar{I}\ Index \cdot 10). \tag{2}$$

By construction, $\bar{I}$ *Index* increases when portfolio diversification rises.

Next, we apply Herfindahl-Hirschman indices (HHIs) as portfolio concentration-risk measures for other loan characteristics. The generic HHI of a portfolio

[6] We multiply the original $\bar{I}$ *Index* by 10 to facilitate the presentation of the results because, otherwise, the regression coefficients become very small. This adjustment affects our results only numerically.

is the sum of the squared shares of its categories j:

$$HHI = \sum_{j=1}^{N} (x_j)^2, \tag{3}$$

where N refers to the total number of distinct categories and x_j is the exposure of category j relative to the portfolio volume. Our empirical analysis utilizes the following modification:

$$HHI^{Adjusted} = \frac{(1 - HHI)}{1 - \frac{1}{N}}, \qquad for\ N > 1. \tag{4}$$

We again refer to the HHI, although we use the adjusted HHI according to Equation 4. When all loans belong to the same category (i.e., concentration risk is highest and diversification lowest), it is equal to zero. When the loan volumes in all categories are equal (i.e., diversification is maximum), its value is one.

Using HHIs, we measure pool diversification across the categories of the Basel concentration risk regulation of pillar II. *Business Type HHI* (2) refers to pool diversification with respect to five distinct obligor legal forms (i.e., public company, limited company, partnership, individual, and other). On average, *Business Type HHI* is 0.42. *Geographic HHI* (3) uses borrowers' one-digit postcodes to account for the contagion effects due to local proximity. In total, our sample consists of 74 different one-digit postcodes and the mean *Geographic HHI* is 0.65. *Industry HHI* (4) is based on borrowers' two-digit NACE industry codes and proxies for industry diversification at the second highest possible level. In our dataset, we observe 88 distinct industries. On average, *Industry HHI* is 0.92.

4.5. Control variables

To account for observable differences between pools, we control for loan, tranche, pool, and bank characteristics. The definitions of the variables and descriptive statistics are shown in Tables 1 and 2. The latter are largely in line with other studies.

Regarding *loan-level characteristics*, we follow Ertan et al. (2017). We calculate these characteristics at the loan level, winsorize the values of continuous variables at 1% and 99%, respectively, and subsequently aggregate them at the pool level using weighted averages (see Section 3.1). *Interest Rate* serves as a proxy for loan riskiness. We further control for loan riskiness by using a collateral indicator variable (*Collateralization*). To account for borrowers' time-varying probability of default, we control for *Loan Years to Maturity*.[7] *Securitized Loan Ratio* serves as a proxy for the period to loan securitization, indicating banks' screening incentives. *Lending Relationship* controls for the effects of an existing relationship between borrower and lender on loan performance.

Regarding *tranche characteristics*, *Tranche Years to Maturity* may signal particularly safe bonds (Helwege and Turner, 1999), while a higher *Number of Tranches* in a securitization transaction may further attract investors and enhance market discipline.

As *pool characteristics*, we specify *Pool Size* to control for size effects. As banks are to specify why a variable is not reported, we can also measure *Information Collection* (e.g., Ertan et al., 2017). *Banking Sector Condition*, based on the number of ABS pools issued in the same year and country, reflects the financial conditions (Affinito and Tagliaferri, 2010) and *Pool Dynamics*[8] accounts for the stability of the ABS loan volume over time.

In our *Pool/Bank Sample*, we additionally observe *bank characteristics* as follows. *Bank Size* measures magnitude, while *Loan Ratio* is a proxy for the business model. Bank exposure to credit risk appears in *NPL Ratio*.

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7 In the robustness tests, we add the variable *Loan Age* and our findings remain the same (see Table A.34 in the online appendix).

8 A growing literature strand deals with the dynamics of securitization and focuses on collateralized loan obligations backed by corporate loans. However, providing a detailed summary of this literature strand is beyond the scope of this paper. As such, we collect background information on the dynamics of securitized loan pools in Table A.8 in the online appendix.

4.6. Empirical strategy

Examining the effects of transparency on securitization pools, we use the endogenous variables described above. With the exception of *Number of Days in Delinquency*, all are, by construction, restricted to the interval between zero and one. Due to their bounded nature, it is inappropriate to implement an ordinary least squares (OLS) regression model. Therefore, we apply a fractional response regression model which is used in several studies and which is particularly suitable for modeling variables bounded to the interval [0, 1] by ensuring the predicted values lie within the unit interval.[9] The log-likelihood function is of the following form (Papke and Wooldridge, 1996):

$$lnL = \sum_{i=1}^{N} y_i ln\{G(x_i'\beta)\} + (1 - y_i) ln\{1 - G(x_i'\beta)\}, \qquad (5)$$

where N is the sample size, y_i is the dependent variable, $x_i'\beta$ reflects the OLS regression model, and $G(.)$ satisfies $0 < G(w) < 1$ for all $w \in \mathbb{R}$. We apply the probit function as the functional form of $G(x_i'\beta)$. Furthermore, we use robust standard errors clustered with respect to the ABS pool, as well as reporting quarter and country FE. Clustering is important, as we observe the same ABS pool several times in our samples and thus control for correlations within one ABS pool over time. The FE incorporate unobserved dynamics over time, as well as the variations between securitization markets and economic conditions at the national level.

5. Empirical results

5.1. Results for pool performance (first regression model)

Baseline regression

Based on the *Pool Sample*, we analyze the impact of transparency on pool

[9] In the robustness tests, we also employ OLS models and obtain qualitatively the same results as by our baseline regressions (see Table A.35 in the online appendix).

performance and estimate the following pooled regression model on quarterly data:

$$\begin{aligned} Pool\ Performance_{ipt} = \alpha &+ \beta \cdot Transparent\ Pool_{it} \\ &+ \gamma' \cdot Loan\text{-},\ Tranche\text{-},\ and\ Pool\text{-}Level\ Controls_{it} \\ &+ \tau' \cdot Reporting\ Quarter_t + \omega' \cdot Country_i + \epsilon_{ipt}, \end{aligned} \tag{6}$$

where i refers to pools, p to pool performance measures, t to quarters, and ϵ_{ipt} is the error term. Loan-, tranche-, and pool-level controls include *Interest Rate*, *Collateralization*, *Loan Years to Maturity*, *Securitized Loan Ratio*, *Lending Relationship*, *Tranche Years to Maturity*, *Number of Tranches*, *Pool Size*, *Information Collection*, *Banking Sector Condition*, and *Pool Dynamics*. *Reporting Quarter* and *Country* represent the time and country FE. We expect the coefficient on *Transparent Pool* (β) to be negative.

Table 3 presents the results of our first baseline regression model. In specifications (1), (2), and (5), we find a negative and significant coefficient on *Transparent Pool*. On average, transparent pools experience lower *Loss Rates* by around 2.3 percentage points (pp), 5.5 pp lower *Default Rates*, and 24% lower *Number of Days in Delinquency* compared to non-transparent pools, which translate to around 55% of the mean *Loss Rate*, 39% of the mean *Default Rate*, and 1.2 days in delinquency with a mean of 2.6 days, respectively. In specifications (3) and (4), *Transparent Pool* also exhibits a negative, but insignificant coefficient.

The control variables' coefficients are predominantly consistent with our expectations. Among loan-level controls, *Collateralization* and *Securitized Loan Ratio* show the highest significance and predominantly indicate that the ABS pools with a higher proportion of collateralized loans and loans directly securitized after loan origination perform better on average. For the tranche and pool characteristics, pools that are issued under a poor *Banking Sector Condition* perform significantly worse in specifications (1), (2), and (5). The variable *Pool Dynamics* indicates that the higher the ratio of new loans introduced into already-securitized asset pools every quarter is, the better the pools tend to

Table 3: Impact of transparency on pool performance (baseline regression)

	Loss Rate	Default Rate	Rate of Del. Amounts	Rate of Del. Loans	Number of Days in Del.
	(1)	(2)	(3)	(4)	(5)
Transparent Pool	-0.0229**	-0.0546**	-0.00323	-0.0265	-0.238**
	(0.0095)	(0.0272)	(0.0037)	(0.0238)	(0.0961)
Interest Rate	-0.00936	-0.00620	-0.00321	-0.0261*	-0.0955*
	(0.0070)	(0.0147)	(0.0023)	(0.0144)	(0.0509)
Collateralization	0.0527	0.232***	0.0255**	0.105*	0.276*
	(0.0356)	(0.0664)	(0.0099)	(0.0574)	(0.1554)
Loan Years to Maturity	-0.0291	-0.00162	-0.0195**	-0.00256	-0.128
	(0.0221)	(0.0490)	(0.0084)	(0.0481)	(0.0959)
Securitized Loan Ratio	0.0624	-0.0434	0.0357***	0.176***	0.487**
	(0.0429)	(0.0661)	(0.0136)	(0.0628)	(0.1954)
Lending Relationship	0.0354	0.0742	0.00906	0.0572	0.142
	(0.0249)	(0.0747)	(0.0124)	(0.0616)	(0.1520)
Tranche Years to Maturity	-0.0334	-0.127**	-0.000482	0.0104	-0.0854
	(0.0259)	(0.0523)	(0.0081)	(0.0519)	(0.1429)
Number of Tranches	-0.00729***	-0.00839***	-0.000579	-0.00192	-0.0142**
	(0.0025)	(0.0029)	(0.0008)	(0.0035)	(0.0055)
Pool Size	0.0114**	0.0470***	-0.000645	-0.00812	0.00792
	(0.0048)	(0.0123)	(0.0021)	(0.0116)	(0.0379)
Information Collection	-0.0322	-0.132	-0.0356*	-0.110	-0.692
	(0.0560)	(0.1221)	(0.0182)	(0.1403)	(0.4509)
Banking Sector Condition	0.0257***	0.0646***	0.00306	0.00146	0.216**
	(0.0080)	(0.0235)	(0.0031)	(0.0208)	(0.0912)
Pool Dynamics	-0.0698***	-0.146*	-0.0206***	-0.103***	-0.270***
	(0.0205)	(0.0770)	(0.0070)	(0.0344)	(0.0868)
Reporting Quarter FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
N	1,072	1,072	1,072	1,072	1,072
Adj. R^2	0.1193	0.1443	0.0898	0.1088	0.4945

This table reports the analysis on whether transparency affects pool performance. Variables are described in Table 1. Specifications (1) to (4) are estimated by a fractional response regression model. The fifth specification is estimated by an OLS regression model. Due to a variance matrix which is nonsymmetric or highly singular in case of specifications (3) and (4), standard errors of these regression models are estimated by means of bootstrapping 500 times. Marginal effects are reported and robust standard errors that are clustered with respect to the ABS pool are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

perform on average. In summary, under transparency, banks seem to securitize better-performing ABS pools in terms of *Loss Rate*, *Default Rate*, and *Number of Days in Delinquency.*

When we adjust the *Transparent Pool* definition in our first regression model and use six (instead of eight) quarters as the maximum period for ABS pools to be classified as non-transparent, *Transparent Pool* still significantly lowers *Loss Rates*, *Default Rates*, and *Numbers of Days in Delinquency.* Furthermore, if we assume maximum time periods for ABS pools that are greater than eight quarters to be classified as non-transparent or if we do not apply any maximum time period, resulting in a static definition of *Transparent Pool*, our results remain robust (see Table A.9 in the online appendix).

Subsample analysis

Banks may change their securitization behaviors over time, which could cause a shift in pool performance that we cannot control for sufficiently by using country and reporting quarter FE. Therefore, we limit our sample to pool observations from the third quarter of 2012 to the second quarter of 2013, which correspond to the ABS loan-level reporting initiative's starting period (see Figure A.2 in the online appendix). Accordingly, we drop 956 of the 1,072 pool observations. With 49% of observations referring to transparent pools, our subsample is almost balanced. As shown in Table 4 (upper panel), *Transparent Pool* significantly improves the pool performance in specifications (1), (4), and (5) and the economic significance relative to our baseline regression increases. Furthermore, the coefficients on *Transparent Pool* in specifications (2) and (3) are consistently negative, but insignificant. The results of our subsample analysis show that the impact of transparency on pool performance is likely not driven by the changes in bank securitization behaviors over time.

Matching analysis

Regarding the differences between transparent and non-transparent pools, we additionally use an exact matching procedure following Ioannidou and Ongena (2010). We first match pools reported in the same year and issued in the same country, also considering the control variables specified in our baseline regres-

Table 4: Impact of transparency on pool performance and diversification (subsample analysis)

	Pool performance				
	Loss Rate	Default Rate	Rate of Del. Amounts	Rate of Del. Loans	Number of Days in Del.
	(1)	(2)	(3)	(4)	(5)
Transparent Pool	-0.0462**	-0.0523	-0.00837	-0.0977**	-0.478**
	(0.0214)	(0.0562)	(0.0055)	(0.0424)	(0.1798)
Controls	Yes	Yes	Yes	Yes	Yes
Reporting Quarter FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
N	116	116	116	116	116
Adj. R^2	0.1874	0.2098	0.0928	0.0858	0.5575

	Pool diversification			
	$\bar{I}$ Index	Business Type HHI	Geographic HHI	Industry HHI
	(1)	(2)	(3)	(4)
Transparent Pool	0.0172***	0.162	-0.0700	0.0709***
	(0.00578)	(0.164)	(0.0430)	(0.0190)
Controls	Yes	Yes	Yes	Yes
Reporting Quarter FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N	79	79	79	79
Adj. R^2	0.1407	0.1734	0.1185	0.2240

This table reports the analysis on whether transparency affects pool performance (upper panel) and pool diversification (bottom panel) in the period from Q3/2012 to Q2/2013. Variables are described in Table 1. Specifications (1) to (4) in the top and bottom panel, respectively, are estimated by a fractional response regression model. The fifth specification is estimated by an OLS regression model. Due to a variance matrix which is nonsymmetric or highly singular in case of specification (2) in the bottom panel, standard errors of this regression model are estimated by means of bootstrapping 500 times. Marginal effects are reported and robust standard errors that are clustered with respect to the ABS pool are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. We report the complete regression results for all control variables in Tables A.10 and A.12 in the online appendix.

sion. Second, we pay attention to the time dimension inherent in our definition of *Transparent Pool* and also require that matched pairs exhibit a maximum difference of two years between their issue dates. Under both approaches, we calculate the spreads between the endogenous variables for each matched pair and regress them on a constant by applying clustered standard errors at the country level. The negative and significant constant terms across all specifications indicate transparent pools perform better than their non-transparent but very similar counterparts (see Table 5, upper panel).

Within ABS pool analysis

Next, to address the potential concern that our results may be driven by unobserved pool and bank characteristics, we focus on ABS pools that change from non-transparent to transparent during the sample period. Particularly, we extend our baseline regression model by pool FE and thus focus on changing originator behavior by exploiting the elimination of inter-pool variation in our sample. Changes in bank behavior can affect pool performance, as most ABS pools in our sample are not static over time (see Section 4.2). Despite these dynamics but in accordance with the nature of securitization transactions, our control variables at the loan, tranche, and pool levels do not vary substantially over time. Consequently, we only employ the interaction term between reporting quarter FE and country FE to control for variations over time as accurately as possible. As reported in Table 6 (upper panel), the results are statistically more significant than in the baseline regression model. *Transparent Pool* significantly lowers all five pool performance measures, indicating that originating banks changed their securitization behavior within one ABS pool due to the introduction of the new transparency regulation.

Non-selective disciplining effects

Finally, we analyze whether the novel transparency regime induced disciplining effects for all pools reported to ED, regardless of being classified as transparent or non-transparent. With the ECB's loan-level reporting initiative, originators are able to monitor the reported data from many other originators and assess the quality of competing ABS pools. Originating banks can thus deepen their

Table 5: Matching between transparent and non-transparent pools

	Pool performance									
	Loss Rate		Default Rate		Rate of Del. Amounts		Rate of Del. Loans		Number of Days in Del.	
Matching variables	(1)		(2)		(3)		(4)		(5)	
Loan-level characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tranche- and pool-level characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country and reporting year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pool issue year		Yes		Yes		Yes		Yes		Yes
Number of observations (matched pairs)	91	70	91	70	91	70	91	70	91	70
Spreads with matching	-0.0488* (0.0126)	-0.0311* (0.0087)	-0.0872*** (0.0049)	-0.0505*** (0.0026)	-0.0127*** (0.0006)	-0.00590*** (0.0006)	-0.0805*** (0.0013)	-0.0471*** (0.0023)	-0.467** (0.0629)	-0.322* (0.0947)

	Pool diversification							
	$\bar{I}$ Index		Business Type HHI		Geographic HHI		Industry HHI	
Matching variables	(1)		(2)		(3)		(4)	
Tranche- and pool-level characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Originating bank characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country and reporting year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pool issue year		Yes		Yes		Yes		Yes
Number of observations (matched pairs)	868	335	868	335	868	335	868	335
Spreads with matching	0.0189* (0.0060)	0.00289** (0.0001)	0.295* (0.0970)	0.173 (0.1122)	-0.00232 (0.0024)	-0.0185 (0.0108)	0.0278*** (0.0045)	0.0236 (0.0045)

This table reports our matching analysis between transparent pools and non-transparent ones. We first match pools reported in the same year and issued in the same country, taking also the control variables specified in our baseline regressions into account (see Equations 6 and 7). In our first regression model, loan-, tranche- and pool-level characteristics include *Interest Rate*, *Collateralization*, *Loan Years to Maturity*, *Securitized Loan Ratio*, *Lending Relationship*, *Tranche Years to Maturity*, *Number of Tranches*, *Pool Size*, *Information Collection*, *Banking Sector Condition*, and *Pool Dynamics*. In our second regression model, tranche- and pool-level as well as originating bank characteristics comprise *Tranche Years to Maturity*, *Pool Size*, *Information Collection*, *Pool Dynamics*, *Bank Size*, *Loan Ratio*, and *NPL Ratio*. We define similar ratios for continuous variables by a window of (–SD, +SD). SD refers to the standard deviation. Second, we require additionally that matched pairs exhibit a maximum difference of two years between their issue dates. Following Ioannidou and Ongena (2010), we regress the spreads on a constant and report the coefficient on the constant. Robust standard errors that are clustered with respect to the country are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 6: Impact of transparency on pool performance (within ABS pool analysis and non-selective disciplining effects)

	Within ABS pool analysis				
	Loss Rate	Default Rate	Rate of Del. Amounts	Rate of Del. Loans	Number of Days in Del.
	(1)	(2)	(3)	(4)	(5)
Transparent Pool	-0.0171** (0.0084)	-0.0479** (0.0187)	-0.0103*** (0.0031)	-0.0581*** (0.0165)	-0.162** (0.0660)
Reporting Quarter x Country FE	Yes	Yes	Yes	Yes	Yes
ABS Pool FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
N	1,072	1,072	1,072	1,072	1,072
Adj. R^2	0.2023	0.3302	0.1273	0.1622	0.8632

	Non-selective disciplining effects				
	Loss Rate	Default Rate	Rate of Del. Amounts	Rate of Del. Loans	Number of Days in Del.
	(1)	(2)	(3)	(4)	(5)
Transparent Pool	-0.0354*** (0.0095)	-0.0661** (0.0258)	-0.00830** (0.0039)	-0.0587** (0.0231)	-0.295*** (0.0973)
Number of Previous Reportings	-0.000105*** (0.0000)	-0.000121 (0.0001)	-0.0000370*** (0.0000)	-0.000240*** (0.0001)	-0.000585*** (0.0002)
Reporting Quarter FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
N	1,072	1,072	1,072	1,072	1,072
Adj. R^2	0.1303	0.1471	0.0905	0.1091	0.5140

The upper panel of this table reports the analysis on whether transparency affects pool performance using ABS pool FE. To ensure a stable estimation and preserve all 1,072 observations, we do not drop non-changing pools. Specifications (1) to (4) are estimated by a fractional response regression model. The fifth specification is estimated by an OLS regression model. The bottom panel of this table reports the analysis on whether transparency induces disciplining effects for all pools reported to ED by additionally controlling for *Number of Previous Reportings*. Specifications (1) to (4) are estimated by a fractional response regression model. The fifth specification is estimated by an OLS regression model. Due to a variance matrix which is nonsymmetric or highly singular in case of specifications (3) and (4) in the bottom panel, standard errors of these regression models are estimated by means of bootstrapping 500 times. Variables are described in Table 1. Marginal effects are reported and robust standard errors that are clustered with respect to the ABS pool are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. We report the complete regression results for the bottom panel in Table A.11 in the online appendix.

expertise in ABS risk assessment and may be incentivized to adjust their securitization behaviors to ensure the competitiveness of their own ABS pools. Against this background, we expect pool performance to improve with an increase in the number of reportings to ED and thus include the number of ABS pool reportings to ED prior to the respective pool's reporting quarter (*Number of Previous Reportings*) in our regression model.

In Table 6 (bottom panel), we first observe that a higher *Number of Previous Reportings* leads to significantly better pool performance across all specifications. Originators seem to respond to the increasing average pool performance and the decreasing costs of granular ABS risk assessment by improving their own pool performance. Second, using the increasing *Number of Previous Reportings* over time as a control variable, the impact of *Transparent Pool* on our pool performance measures improves, both statistically and economically. Altogether, the transparency regime has disciplinary effects for all pools, but these effects are even more pronounced for transparent pools.

Finally, from the bank perspective, unreported analyses provide tentative evidence that originating banks seem to manage pool performance by retaining poor-performing loans on their balance sheets. Therefore, better-performing ABS pools may come at a cost, as originating banks' credit risk exposure seems to increase.

5.2. Results for pool diversification (second regression model)

Baseline regression model

In the second regression model, we examine the impact of transparency on portfolio diversification. We use the *Pool/Bank Sample*, as we need to control for both securitization and originating bank characteristics. Incorporating originating bank information is especially relevant, as bank business models vary widely in this sample. For example, the standard deviation of *Bank Size* accounts for EUR 287 billion. This corresponds to the size difference between a large international bank and a local bank operating mainly at the national level.

Additionally, in this second regression model, we adjust our definition of

Transparent Pool. Although the ABS pools observed in our sample are not completely static over time, it is difficult for banks to substantially change the degree of diversification within a short period. Therefore, instead of fixing the maximum time period for ABS pools to be classified as non-transparent, we define transparent pools as those issued after the announcement date of the loan-level reporting requirement for SME loan securitizations in April 2011.[10]

Accordingly, we estimate the following pooled fractional response regression model using quarterly data from the *Pool/Bank Sample*:

$$\begin{aligned} Pool\ Diversification_{idt} = {} & \alpha + \beta \cdot Transparent\ Pool_{it} \\ & + \gamma' \cdot Tranche\text{-},\ Pool\text{-},\ and\ Bank\text{-}Level\ Controls_{it} \\ & + \tau' \cdot Reporting\ Quarter_t + \omega' \cdot Country_i + \epsilon_{idt}, \end{aligned} \tag{7}$$

where i are pools, d pool diversification measures, t quarters, and ϵ_{idt} is the error term. Tranche-, pool-, and bank-level controls include *Tranche Years to Maturity*, *Pool Size*, *Information Collection*, *Pool Dynamics*, *Bank Size*, *Loan Ratio*, and *NPL Ratio*. *Reporting Quarter* and *Country* represent time and country FE, respectively. We expect the coefficient on *Transparent Pool* (β) to be positive.

Table 7 presents the results. In specifications (1), (2), and (4), we find positive and significant coefficients on *Transparent Pool*. Transparent pools exhibit a 0.0088 higher $\bar{I}$ *Index*, 0.188 higher *Business Type HHI*, and 0.0241 higher *Industry HHI*. These translate to 29% of the sample's standard deviation of the $\bar{I}$ *Index*, 72% of the *Business Type HHI* standard deviation, and 34% of the *Industry HHI* standard deviation. Our results reveal that pools issued under the transparency regime are more diversified in terms of single-name concentration risk, business types, and industries.

In specification (3), we observe a significant negative coefficient on *Transparent Pool* when considering *Geographic HHI* as the diversification measure. This

[10] In unreported robustness checks, we relax this modification. For an increasing maximum time period for ABS pools classified as non-transparent, the statistical significance of our results increases. This supports our assumption that originating banks are not able to adjust the degree of diversification in their ABS pools in the short run.

finding somewhat contradicts our results in the remaining specifications. However, *Geographic HHI* is calculated from borrowers' one-digit postcodes and, therefore, the sizes of regions may vary widely both across and within countries. This leads to a limited comparability of geographic diversification.

The results of our second baseline regression model indicate that, under the transparency regime, banks securitize more diversified ABS pools in terms of $\bar{I}$ *Index*, *Business Type HHI*, and *Industry HHI*.

Subsample analysis

Again, a potential concern may be that our results are driven by changes in bank securitization behaviors over time, which we cannot control for sufficiently in our baseline regression. Therefore, we reduce our sample by 501 observations to just 79, by limiting it to the third quarter of 2012 to the second quarter of 2013. In our subsample, 59% of observations refer to transparent pools. As per Table 4 (bottom panel), *Transparent Pool* increases pools' $\bar{I}$ *Index* and *Industry HHI*, with considerable statistical and economic significance. The coefficients on *Transparent Pool* in specifications (2) and (3) lack significance. Overall, the subsample analysis indicates that the impact of transparency on pool diversification is mostly not driven by the changes in bank securitization behaviors over time.

Matching analysis

We further elaborate on the differences between transparent pools and non-transparent ones. First, we only allow matches for pools reported in the same year and issued in the same country, also considering control variables at the tranche and pool level, as specified in our baseline regression. Second, we require a maximum difference of two years between the times of issue for the matched pairs. By calculating the spreads between the endogenous variables for each matched pair, regressing this spread on a constant, and applying clustered standards errors at the country level, we support the outcomes of our baseline regression (see Table 5, bottom panel).

Table 7: Impact of transparency on pool diversification (baseline regression)

	$\bar{I}$ Index	Business Type HHI	Geographic HHI	Industry HHI
	(1)	(2)	(3)	(4)
Transparent Pool	0.00884*	0.188*	-0.0450*	0.0241**
	(0.00518)	(0.107)	(0.0253)	(0.00983)
Tranche Years to Maturity	0.0119	0.148	-0.112	0.00678
	(0.0120)	(0.201)	(0.0896)	(0.0162)
Pool Size	0.00806***	0.00789	0.0483**	-0.0106
	(0.00244)	(0.0522)	(0.0218)	(0.00702)
Information Collection	0.0208	0.451*	-0.0648	-0.0768
	(0.0196)	(0.265)	(0.236)	(0.0536)
Pool Dynamics	0.00859*	-0.0750	0.0308	0.0287**
	(0.00503)	(0.0688)	(0.0387)	(0.0137)
Bank Size	-0.000609	-0.0406	0.0320**	-0.00397
	(0.00176)	(0.0347)	(0.0152)	(0.00310)
Loan Ratio	0.0236*	-0.205	-0.196	0.0155
	(0.0127)	(0.223)	(0.179)	(0.0456)
NPL Ratio	-0.00387	0.489	1.148***	0.298***
	(0.0232)	(0.345)	(0.303)	(0.0963)
Reporting Quarter FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
N	580	580	580	580
Adj. R^2	0.1600	0.1183	0.1260	0.0263

This table reports the analysis on whether transparency affects pool diversification. Variables are described in Table 1. All specifications are estimated by a fractional response regression model. Due to a variance matrix which is nonsymmetric or highly singular in case of specification (2), standard errors of this regression model are estimated by means of bootstrapping 500 times. Marginal effects are reported and robust standard errors that are clustered with respect to the ABS pool are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

6. Competing explanations

We want to ensure that our findings on pool performance and diversification of ABS backed by SME loans are driven by transparency. To this end, we collected several potential confounding events and factors in Europe over the past ten years (see Table A.13 in the online appendix). These include ECB activities, banking sector characteristics, and macroeconomic developments. We incorporate them as further control variables and summarize the main results of the amended baseline regressions in Table 8 and below. The detailed results as well as the descriptions of the additional variables are presented in the online appendix (see Tables A.14 - A.31).

First, the securities to be purchased by the ECB within the ABSPP require certain eligibility criteria. Grosse-Rueschkamp et al. (2019) provide evidence that the ECB's acquisition indeed affects the bond markets, as the announcement of central bank purchases reduces the bond yields of the firms whose bonds are eligible for such purchases. *ABSPP Net Purchases at Reporting (ABSPP Net Purchases at Issue)* refer to ECB's net purchases during the quarter prior to the respective pool's reporting (issue) quarter. We also include *ABSPP Implementation Dummy*, equal to one for all ABS pool observations reported at least one quarter after the ABSPP launch on November 21, 2014, and zero otherwise. Across all three variable definitions, *Transparent Pool* still lowers *Loss Rates*, *Default Rates*, and *Numbers of Days in Delinquencies* significantly. Similarly, the positive impact of *Transparent Pool* on $\bar{I}$ *Index*, *Business Type HHI*, and *Industry HHI*, as well as the negative impact on *Geographic HHI*, are in line with our baseline regressions (see Tables A.14 - A.16 in the online appendix). We also control for ECB's collateral framework, using *ECB Rating Threshold* and *ECB Haircut* as variables, because Van Bekkum et al. (2018) show that a changing rating requirement for ABS to be accepted as collateral affects the European securitization market; nonetheless, our results still hold (see Tables A.17 and A.18 in the online appendix).

Second, focusing on banking sector characteristics, we use variables repre-

Table 8: Possible competing explanations for pool performance and diversification

		Pool performance					Pool diversification				
Confounding factor	Data source	Loss Rate	Default Rate	Rate of Del. Amounts	Rate of Del. Loans	Number of Days in Del.	$\bar{I}$ Index	Business Type HHI	Geographic HHI	Industry HHI	Online appendix
Baseline regression		- -	- -	o	o	- -	+	+	-	++	
ABSPP											
ABSPP Net Purchases at Reporting	ECB	- -	- -	o	o	- -	+	o	-	++	Table A.14
ABSPP Net Purchases at Issue	ECB	- -	- -	o	o	- -	+	+	-	++	Table A.15
ABSPP implementation	ECB	- -	- -	o	o	- -	+	o	-	++	Table A.16
ECB collateral framework											
ECB Rating Threshold	ECB	- -	- -	o	o	- -	+	+	-	++	Table A.17
ECB Haircut	ECB	- -	- -	o	o	- -	+	+	-	++	Table A.18
National securitization regulation and supervision											
Spanish Sec. Regulation	Law No. 5/2015	- - -	- - -	- - -	- - -	- - -	+	+++	o	+++	Tables A.19 and A.20
Skin in the game											
Rate of Retained ABS Volume	SIFMA	- -	- -	o	o	- -	+	o	-	++	Table A.21
Reserve Account	ED	- - -	- - -	o	-	- - -	+++	+	-	+++	Table A.22
Banking sector structure and crisis											
Change in Total Number of Banks (%)	ECB	- -	-	o	o	- -	+	o	-	++	Table A.23
NPL Ratio	Fitch Connect	-	o	-	o	- -					Table A.24
Financial Aid for Italian Banks	EU Commission	o	- - -	o	o	- - -	o	o	o	+++	Tables A.25 and A.26
Lending Standards											
ECB Lending Standard Index	ECB	- -	- -	o	o	- -	+	o	o	++	Table A.27
Country creditworthiness											
Sovereign Bond Yield	FRED	- -	- -	o	o	- -	+	o	-	++	Table A.28
Sovereign Bond Rating	S&P	o	-	o	o	- -	+	o	- -	++	Table A.29
Economic development											
GDP	Eurostat	- -	- -	o	o	- -	+	+	-	++	Table A.30
EURIBOR	ECB	- -	- -	o	o	- -	+	+	-	++	Table A.31

This table reports the regression results of our analysis on whether transparency affects ABS pool performance and diversification, controlling for many different possible confounding factors. +, ++, and +++ denote significantly positive coefficients on *Transparent Pool* at the 10%, 5%, and 1% levels, -, - -, and - - - denote significantly negative coefficients, respectively. o refers to insignificant coefficients. Variables are described in the online appendix (see column 12).

senting national securitization regulation and supervision, skin in the game, banking sector structure and crises, and lending standards. The variables and regression outcomes are shown in Tables A.19 - A.27 in the online appendix. A new Spanish securitization regulation implemented in April 2015 and financial aid for Italian banks between May and July 2017 are two particular cases. For instance, Spain introduced a new securitization regulation as Law No. 5/2015, which among others, strengthens transparency and investor protection requirements. As this restriction only applies locally, we create subsamples containing all 348 Spanish observations in our *Pool Sample* and all 191 Spanish observations in our *Pool/Bank Sample*, respectively. The *Spanish Securitization Regulation* is specified as a dummy variable equal to one for all pools issued after the introduction of the regulation in April 2015. Following the *Transparent Pool* definition in our first regression model, we allow other pools to be classified as non-transparent for a maximum of two years. The impact of *Transparent Pool* on pool performance and diversification of ABS backed by SME loans, except for *Geographic HHI*, increases in significance.

Third, we incorporate different macroeconomic developments across countries and over time. Motivated by the sovereign debt crisis and the low interest rate environment, we control for country creditworthiness (*Sovereign Bond Yield* and *Sovereign Bond Rating*), *GDP*, and *EURIBOR*. Our results continue to hold, as we qualitatively obtain the same impact of *Transparent Pool* in all robustness checks (see Tables A.28 - A.31 in the online appendix).

In a final robustness check, we replace *Transparent Pool* by a new binary variable, which randomly assigns values of one (transparent pool) or zero (non-transparent pool) to observations. We then estimate our baseline regressions 1,000 times, with different sets of transparent and non-transparent pools. Assume *Transparent Pool* was *not* the major driver of our results due to unobserved confounding factors that systematically affect our results but cannot sufficiently be controlled for. Then, the effects of the new randomly drawn variable should be similar to the outcomes of our baseline regressions. However, this procedure mostly reveals insignificant and symmetrically distributed coefficients on the new variable, indicating that the effects of *Transparent Pool* are not driven by unobserved confounding factors (see Table A.32 in the online appendix). Although all our robustness tests support the empirical results, we acknowledge they are not sufficient to claim causal effects.

7. Conclusions

A lack of transparency arguably exacerbated the slowdown of securitization markets during the financial crisis. Consequently, the ECB launched the loan-level reporting initiative, obliging originators to disclose quarterly loan-by-loan information for ABS used as collateral in Eurosystem credit operations to a broad range of market participants. Our study empirically explores whether this novel ABS reporting requirement has had favorable effects on securitization pools. In particular, we consider whether originators really improve their ABS pool performance and diversification. Pool-level, rather than loan-level, analyses are particularly relevant, because most observed ABS pools are not entirely static over time and diversification can only be addressed at the pool level.

We obtain data from ED, the central repository of all loan-level information under ECB's loan-level reporting initiative and use several fractional response regression models. By applying reporting quarter, country, and partially, ABS pool FE, our results suggest the novel transparency regime indeed has valuable effects for investors. Specifically, pools affected by the novel transparency regime perform better, that is, show significantly lower loss rates, default rates, rates of delinquent amounts, rates of delinquent loans, and include loans with fewer days in delinquency on average. Furthermore, pools affected by the transparency regime are more diversified than others with respect to single-name concentration, business types, and industries.

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