Securitization, Covered Bonds and the Risk Taking Behavior of European Banks

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Keywords: Securitization, Covered Bonds, Credit Risk, European Banks, Risk Retention, Propensity Score Methods

JEL Classifications: G01, G21, G23

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Securitization, Covered Bonds and the Risk Taking Behavior of European Banks

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Abstract

This study investigates the impact of securitization and the issuance of covered bonds on the credit risk taking behavior of banks. We collected data for seven major European economies for the period between 2001 and 2014, that is, both before and after the global financial crisis of 2008. In this paper. we address self-selection concerns about the endogeneity of the decision to securitize or issue covered bonds by using the Covariance Balancing Propensity Score method. We inquire whether securitizing banks hold portfolios that contain riskier assets than those of banks that issue covered bonds and whether the risk taking behavior of banks changed after the recent financial crisis. Our results suggest that European banks typically view securitization as a financing rather than a risk management tool. Therefore, our findings do not support the conventional wisdom that the absence of skin in the game causes banks to assume more risk. Instead, we find evidence that securitizing banks have been opting for lower risk asset portfolios after the 2008 crisis.

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1. Introduction

Securitization is one of the most important innovations in financial markets. Through securitization, banks can convert illiquid assets into liquid securities that can be sold to dispersed investors. As a result, securitization improves liquidity in the capital markets and allows originators to remove issued loans from balance sheets, applying the proceeds to other purposes (DeMarzo, 2005; Coval et al., 2009). Asset-Backed Securities (ABS), that pool various types of securities with different classes of risk and return in the form of tranches in order to stoke investor demand, are attractive for many participants in the financial markets.

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Despite these advantages, securitization[1] is often considered to be one of the main causes of the recent financial crisis. The standard design of ABS appears to violate fundamental incentive conditions (Cerasi and Rochet, 2014). Without a deductible of sufficient size, the originators of credit securitization have no incentive to screen loan applicants appropriately. They are not interested in monitoring the loan contract strictly because they do not have enough *skin in the game* (Keys et al., 2010).

This view of securitization influenced policy on both sides of the Atlantic after the 2008 global financial crisis (GFC). According to the U.S. regulatory authorities, moral hazard and inadequate monitoring can be mitigated if originators retain the underlying assets on their balance sheets (Pinedo and Tanenbaum, 2010), which would align their incentives with those of investors[2] thus improving loan-origination practices. Covered Bonds (CBs), a close on-balance-sheet analog of ABS, are supposed to serve this purpose. If risk retention makes a difference, CB-issuing banks should refrain from taking imprudent risks.

Our study aims to ascertain whether securitizing banks hold portfolios that contain riskier assets than those of banks that issue CBs. It also inquires whether the risk-taking behavior of banks changed after the 2008 financial crisis when banks began issuing more CBs than ABSs. We probe these questions by studying the impact of securitization and CBs on the credit risk taking behavior of European banks.

Previous studies of the effects of securitization have yielded inconclusive results. The assertion that securitization leads to moral hazard, thereby making issued loans riskier, has been questioned (Gorton, 2009b; Gorton and Souleles, 2007; Le et al., 2016). In fact, as highlighted by Gorton (2009a), mortgage lenders and securitizers have developed a range of practices to mitigate the moral hazard, including contractual provisions as well as software systems that automate mortgage underwriting.

The results of the extant empirical studies are also inconsistent. First, the methodology of some of those studies has recently been challenged. This challenge has been directed at the most prominent empirical works on the impact of securitization on lending standards (Keys et al., 2009, 2010, 2012). The theory that animates those papers proceeds from the assumption that securitizers employ a rule of thumb that is based on FICO scores[3] because they are exogenously more willing to purchase loans extended to borrowers with FICO scores just above 620. The authors of the studies in question exploited this discontinuity to devise a natural experiment in order to learn about the moral hazard effect of securitization on lender screening. Bubb and Kaufman (2014) criticized these works and provided evidence that, absent changes in the probability of securitization, lenders change their screening practices at credit-score cutoffs. Since FICO score can affect the screening incentives of a lender,[4] changes in screening are not necessarily linked to securitization. Second, most of the studies in question focus on the U.S. market, and their

[1]The terms “securitization” and “asset-backed securities” are used interchangeably here.

[2]Similar views have been expressed in the context of European reform — see the risk-retention requirements in the Capital Requirement Regulations (CRR) Directive.

[3]A FICO score is a credit score that was created by the Fair Isaac Corporation (FICO). FICO scores range between 300 and 850. In general, scores in the 670-739 range are indicative of a “good” credit history, and most lenders will consider it favorable. In contrast, borrowers in the 580-669 range may find it difficult to obtain financing at attractive rates.

[4]For instance, the lender may rely on a high FICO score and not screen the borrower properly.

results cannot be generalized to other countries. For example, the subprime mortgage market is largely non-existent in Europe. Third, an important issue that arises when one tries to estimate the effect of securitization on bank portfolios is that the choice to securitize may be endogenous — banks decide whether they want to access this market autonomously.

Here, we adopt a different approach. We consider securitizing banks and CB-issuing banks, and we compare the riskiness of their loan portfolios in the periods before and after the 2008 financial crisis. We address self-selection concerns about the endogeneity of the decision to securitize or issue CBs by using the Covariate Balancing Propensity Score (CBPS) method,[5] which is considered to be more robust than traditional propensity score based methods because it improves the covariate balance across treatment groups.

Our paper makes a threefold contribution to the literature. First, it focuses on the European securitization market, which is relatively under investigated. Second, CBs have largely been neglected in the academic literature. Our study is an attempt to fill the resultant gap. Thus, we try to understand the role of on balance sheet risk retention in shaping the credit risk taking behavior of banks. Finally, we offer a methodological contribution, in that we address the self selection issue (the endogeneity of the decision to issue ABSs or CBs) by using a doubly robust (DR) treatment effect estimator.

The rest of the paper is structured as follows. Section 2 reviews previous research in the field, focusing on securitization and CBs. Section 3 describes and discusses our research methodology. Section 4 provides detailed results and explains the main findings. Section 5 concludes.

2. Related literature

Securitization has been studied extensively, especially after the eruption of the GFC. Conversely, CBs have attracted little attention in the academic literature. However, the market developed a strong appetite for CBs after the GFC, and they came to be treated as the main alternative to securitized products. Our work is related to both strands of the literature.

2.1. Securitization

A number of theoretical and empirical studies have shown that securitization leads to lax lending standards (Keys et al., 2010, 2012). Loan sales may create moral hazard and adverse selection problems because they affect the incentive of the bank to monitor borrowers (Elul, 2015). The explanation is simple. Most of the information that a bank uses during the loan-origination process is not transmitted to the market. As a result, that bank may have an incentive to securitize low-quality loans. At the same time, it lacks incentives to screen borrowers properly at the point of origination or to monitor them continuously thereafter (Morrison, 2005). Purnanandam (2011) reached a similar conclusion. He provided evidence that the lack of screening incentives, coupled with leverage-induced risk-taking behavior, contributed significantly to the subprime mortgage crisis. Bord and Santos (2015) suggested that the banks that adopted lax underwriting standards were aware of the attendant risk because they were charging higher interest

[5]To the best of our knowledge, this is the first study that uses CBPS in a finance paper.

rates. They found that the share of retained securitization on the portfolio of a bank is also important — loans issued by banks with higher retention rates performed better.

The study by Kara et al. (2016) provides further interesting results. The authors found that loans with a higher default risk have a lower probability of being securitized. However, once these high-quality loans are sold to investors, the banks' incentive to monitor their borrowers continuously is reduced. The lack of monitoring causes the performance of loans that are initially considered to be of high quality to deteriorate. These results support common intuitions about the relationship between securitization and monitoring incentives (Bord and Santos, 2015).

Some studies have arrived at different conclusions. In Chiesa (2008, 2015), it emerged that credit-risk transfers through securitization are not necessarily linked to the distortion of monitoring incentives. On the contrary, the adroit use of securitization may enhance monitoring incentives, and the observed defaults could be attributed to the state of the economy. Therefore, the decision to issue a specific type of security is irrelevant to determining the level of credit risk that a bank has assumed. Instead, it depends on economic and market conditions.

Similarly, Bonner et al. (2016) found that securitization reduces risk taking by banks because of the high risk aversion that European financial institutions and investors exhibit and because of the existence of regulatory incentives to issue more high-quality mortgages and securitized products. Likewise, Casu et al. (2011) argued that banks understand the risks of securitized pools of assets and become more risk averse in response to them. Accordingly, they retain less risky assets and allocate capital to portfolios of assets with a lower credit risk. The authors supported their theory with empirical evidence and tied their observations to the recourse hypothesis, that is, to the fact that originators provide implicit or explicit recourse to the securitization structures known as Special Purpose Vehicles (SPVs). Implicit recourse can be provided by selling assets to an SPV at a discount, purchasing assets from the SPV at a price that exceeds their fair value, replacing nonperforming assets with performing ones, and providing credit enhancement beyond contractual undertakings[6]. The empirical investigation that Ambrose et al. (2005) carried out confirms that high-risk loans are retained by banks and that low-risk loans are securitized. The retention of high-risk loans prevents monitoring incentives from being distorted, and securitization is not driven by a desire to shift risks. The results confirm that firms hold assets in securitized forms in order to minimize the burden of regulatory capital requirements, that is, for purposes of regulatory capital arbitrage. Ultimately, securitized loans are expected to be safer.

2.2. *Covered Bonds*

ABS and CBs should provide similar economic benefits to investors (IOSCO, 2012). A bank, having originated assets, places them into a pool. The securities that are issued and ring fencing practices may vary between security types and countries, but the assets always serve as collateral for the issued securities (ABS or CBs). However, unlike in securitization, when CBs are issued, the collateral remains on the balance sheet of the issuer. Moreover, the issuing institution states explicitly that the ring fenced assets are

[6] See Gorton and Souleles (2007) for further details.

separate and that they are held against the CBs[7].

That CBs remain on the balance sheets of banks is supposed to maintain the incentive to monitor and screen borrowers (Pinedo and Tanenbaum (2010)). Therefore, CBs are a secure investment because they entail many layers of protection. At the same time, they serve as a stable source of funding for issuers, who can sell them to investors or central banks (Murphy, 2013). They offer greater transparency than securitized products because the information-asymmetry problem, which is often associated with securitization, is far less pronounced in the case of CBs. All these characteristics generate strong incentives for issuers-originators to underwrite prudently, which is perceived as the primary advantage of CBs over securitized products (Surti, 2010). If CBs are mainly issued to meet liquidity requirements and to control funding costs (and not to transfer credit risk or to engage in regulatory capital arbitrage (Cardone-Riportella et al., 2010), their issuance should not affect the credit-risk-taking behavior of a bank. In our analysis, we first concentrate on the determinants of securitization and CB issuance in the European market. Then, we try to understand how they affect the risk-taking behavior of banks.

3. Research methodology

In this paper, we evaluate the impact of engaging in securitization or issuing CBs on the risk-taking behavior of banks. In econometric terminology, we want to measure two treatment effects on an outcome variable. The two treatments are the decision of a bank to either securitize or issue CBs, and the outcome is a measure of risk-taking behavior. The banks that make these decisions form two distinct treated groups; those that make no such decisions form a control group.

The main methodological issue that we need to address is the self-selection mechanism that results from the endogeneity of the decision to securitize or issue CBs[8]. Self-selection into one of the treatments could be related to observable characteristics, unobservable characteristics, or both. The selection of appropriate statistical and econometric tools for attenuating selection bias in treatment-effect estimations depends on the nature of the causes of that bias. The approach that is adopted in this paper combines the DR estimators developed by Robins and Rotnitzky (1995) and the difference-in-difference methods that have been popularized in economics by Ashenfelter and Ashenfelter and Card. The former are recommended by Imbens and Wooldridge (2009, sect. 5.6) as robust tools for handling the selection on observables, while the latter account for the selection on unobservable time-invariant bank characteristics.

[7]In some European countries, the assets that are held against the issued CBs are recorded in a register. An independent monitoring institution ensures that the covered pool is well maintained at all times and that all the necessary adjustments are made on time and recorded in the register. This monitoring institution also issues certificates prior to the issuance of CBs. The institution in question thus plays an important role in maintaining the confidence of investors and ensuring the stability of the CB market.

[8]If the risk-taking behavior of banks were different across the three groups even in the absence of treatments, say because banks in different groups are systematically heterogeneous in respect of some of their characteristics, it would be impossible to estimate the effects of securitization or issuing CBs simply by comparing the change in performance before and after the treatment of treated and control banks, as in the standard difference-in-difference approach. Instead, we would need to estimate the unobserved outcome for each bank if it had elected to take a different decision, that is, to estimate counterfactual outcomes.

The DR treatment-effect estimators are based on a preliminary estimation of propensity scores (PS), i.e., probabilities of receiving one of the treatments conditional on a set of pretreatment covariates. It is well known that the performance of any TE estimator that is based on PSs depends crucially on the quality of the estimates of the latter—a small misspecification of the PS model tends to generate significant bias in the treatment-effect estimates (see Smith and Todd, 2005). To further robustify our results, we estimate the PS by using two recent methodologies, CBPS by Imai and Ratkovic (2014) and Generalised Boosted Models (GBM) Generalized by McCaffrey et al. (2004)[9] While CBPS and GBM originate from very different specification strategies (CBPS is a parametric method; GBM is a nonparametric one), both are seen as quite robust. By optimizing the covariate balance across treated and control groups, which is one of the crucial conditions for the validity of PS methods, they mitigate the negative effects of the potential misspecification of the PS model on the treatment-effect estimates. Moreover, they can handle the multinomial nature of the treatment status that we consider easily.

The next sections provide additional details on the components of our TE estimation methodology.

3.1. The setup

We consider a sample of banks, indexed $i = 1, 2, \ldots, N$, which might decide to securitize, issue CB or do nothing. For both treatments, we consider only banks which conducted a transaction for the first time during the sample period. For each bank our observations center around the year, denoted by t_i, in which we observe the bank's treatment status. Since the observation date is specific to each bank, the sample is a cross section. To simplify our notation, we index the observed variables using the bank's index i and a second index equal to $t + h$ in order to denote the available observations at date $t_i + h$.[10] Let W_i be a categorical variable that indicates whether, in period t bank i securitized ($W_{it} = 1$), issued CB ($W_{it} = 2$) or did neither of the two ($W_{it} = 0$). Let us denote the treatment outcome with $\Delta y^{(w)}_{it+h}$, a measure of the change in the credit-risk-taking behavior of bank i between years $t-1$ and $t+h$ if it was subject to treatment w in year t. In order to differentiate between short- and long-run effects, we consider $h = 1$ and $h = 3$. In general, we are interested in the estimation of the following average treatment effects (ATEs):

$$\begin{aligned}\tau_h^{SEC} &= \mathrm{E}\left(\Delta y^{(1)}_{it+h} - \Delta y^{(0)}_{it+h}\right)\\ \tau_h^{CB} &= \mathrm{E}\left(\Delta y^{(2)}_{it+h} - \Delta y^{(0)}_{it+h}\right)\end{aligned}$$

which denote the expected $(h+1)$-period effect of securitization or issuing CBs relative to issuing neither on a bank that is drawn at random from the population. It should be noted that the data contains observations of $\Delta y^{(W_i)}_{it+h}$ only - in the terminology of Rubin (1974) potential outcomes model, the outcomes for the remaining two treatment levels

[9]In this paper, we focus mainly on the results obtained with the former, and we consider the latter as a robustness check.

[10]In other words, we omit the i index for the date at which we observe bank's i decision. Note that these observation dates are generally different across banks.

are counterfactuals and are never observed. This means that τ_h^{SEC} and τ_h^{CB} cannot be estimated directly. Under some assumptions, however, they are identified and can be recovered from nonexperimental data.

The first common assumption in the literature on treatment-effect estimation is the *Stable Unit Treatment Value Assumption* (SUTVA, see Rubin, 1978), according to which the treatment selection decision of a bank has no effect on the outcome for any other bank in the population. In other words, the outcome for any bank is only affected by the treatment it receives. Importantly, the SUTVA rules out the possibility of the securitization or CB issuance decisions of individual banks producing general equilibrium effects.

The identification of ATEs hinges on the validity of two other assumptions, the *Conditional Independence Assumption* (CIA) and the *Common Support Assumption*. The CIA (Rubin, 1977) states that the potential outcomes $(\Delta y^{(0)}_{it+h}, \Delta y^{(1)}_{it+h}, \Delta y^{(2)}_{it+h})$ are independent of the treatment assignment W_{it} conditionally on a vector of pretreatment covariates X_{it-1}. In our framework, this proposition can be formalized as follows:

$$\Delta y^{(0)}_{it+h}, \Delta y^{(1)}_{it+h}, \Delta y^{(2)}_{it+h} \perp\!\!\!\perp W_{it} \mid X_{it-1}. \tag{1}$$

In a nutshell, the CIA assumes that banks that are characterized by different treatment levels are indistinguishable after conditioning on X_{it-1}. This assumption, which is also referred to as "unconfoundedness" or "selection on observables", attributes any systematic difference in outcomes to the effect of the treatment.

The unconfoundedness assumption (1) can, in principle, be used to develop methods based on regression or matching to estimate the ATE of interest. When the dimension of X_{it-1} is large, however, these approaches tend to become impractical. The analysis is simplified considerably by the use of an important result from Rosenbaum and Rubin (1983): under the assumption (1), the independence of the potential outcomes and the treatment indicator also holds if we condition on the vector of PSs, i.e., on the probabilities of each treatment conditional on the pretreatment covariates X_{it-1}:

$$\begin{aligned} & \Delta y^{(0)}_{it+h}, \Delta y^{(1)}_{it+h}, \Delta y^{(2)}_{it+h} \perp\!\!\!\perp W_{it} \mid X_{it-1} \\ \Rightarrow \quad & \Delta y^{(0)}_{it+h}, \Delta y^{(1)}_{it+h}, \Delta y^{(2)}_{it+h} \perp\!\!\!\perp W_{it} \mid p_0(X_{it-1}), p_1(X_{it-1}), p_2(X_{it-1}) \end{aligned} \tag{2}$$

In light of this result and under (1), unbiased estimates of ATE can be obtained by comparing outcome levels between groups of observations that have homogeneous PSs. This simplifies the analysis considerably since, in most applications, the number of PSs, which is the same as the number of treatments, is much smaller than that of relevant pretreatment variables in X_{it-1}.

PSs can be used to estimate ATE of interest in a variety of ways, such as by considering them as covariates in a parametric or nonparametric regression analysis, by stratifying the sample into groups within which the treatment can be considered to be assigned with (approximately) equal probability, or by weighting individual observations to recover expected potential outcomes under each treatment. In this paper, we use an approach that combines regression and PS weighting in the class of DR estimators that was developed in Robins and Rotnitzky (1995), and which was described briefly in section 3.2. It is important to note, however, that despite their well-known robustness and flexibility, DR estimators

— like all PS-based methods — are appropriate only if the self-selection of banks into their respective treatments can be fully explained by their pretreatment covariates X_{it-1}. This is a very stringent condition, and it is unlikely to be met often in practice. In order to account for unobservable differences between banks at least partially, we estimate the ATE by using the change in the credit-risk-taking behavior of banks before and after the treatment as an outcome variable. This enables us to remove the confounding effect of any unobservable time-invariant bank characteristics, thus enhancing the robustness of the ATE estimates.

The second requirement for identifying the ATE is that the CSA must also be borne out.

$$0 < p_w(x) = \text{Prob}(W_{it} = w | X_{it-1} = x) < 1, \quad \text{for } w = 0, 1, 2 \text{ and } \forall x. \tag{3}$$

Assumption (3) states that, whatever the value of the covariates in $t-1$, there is a positive probability of each treatment being observed in t. This, in turn, implies that, given a treatment level, the support of the distribution of the pretreatment covariates overlaps fully across treatments.

3.2. The doubly-robust TE estimator

The DR estimators developed in Robins and Rotnitzky (1995) and Robins et al. (1995) are widely considered to be among the most robust econometric tools for estimating ATE. For this reason, they are generally recommended in practice (see Imbens and Wooldridge, 2009). The implementation of the DR estimators proceeds in two steps. In the first, one assumes a functional form for the population PSs $p_w(x)$ and computes the corresponding estimates $\widehat{p}_w(x)$[11]. In the second step, we use a weighted linear regression model for the change in the risk-taking behavior of banks, with weights allocated by reference to the inverse of the estimated conditional probabilities of the observed treatments. The objective function to be minimized is given by the weighted sum of the squares.

$$\sum_{i=1}^{N}\sum_{w=0}^{2}\frac{\mathbb{I}(w = W_{it})}{\widehat{p}_w(X_{it-1})}\left[\Delta y_{it+h} - \beta_0 - \tau_h^{SEC}\mathbb{I}(w=1) - \tau_h^{CB}\mathbb{I}(w=2) - X'_{it-1}\beta\right]^2, \tag{4}$$

where $\mathbb{I}(c)$ denotes the binary indicator function, equal to 1 if condition c is valid, and 0 otherwise.

Unlike methods based on averaging the observed outcomes that are weighted by the inverse estimated PSs, the DR estimators are not asymptotically efficient. The reason for combining weighting and regression lies in the robustness of the resulting ATE estimators. As discussed by Imbens and Wooldridge (2009), DR methods provide consistent estimators of an ATE when at least one of the specifications, be it the conditional expectation of the outcome or the PS equation, is correct.

[11]Frequently $pw(x)$ is estimated by maximum likelihood. In this paper, we use two recent alternative strategies, CBPS and GBM, which will be discussed on the following pages.

3.3. PS estimation by CBPS

The implementation of the DR estimator requires that the PSs $p_w(x)$ be estimated. In this section, we discuss the CBPS approach Imai and Ratkovic (2014), which will be used to obtain the ATE estimates that we discuss in subsequent sections. An alternative approach,GBM by McCaffrey et al. (2004), will be considered as a robustness check in section 4.4.

CBPS starts with a simple parametric assumption of a multinomial logit structure about population PSs. For the three-valued treatment that is of interest in this paper, those are given by the following equation:

$$p_w(x;\beta) = \begin{cases} \dfrac{1}{1+\sum_{\ell=1}^{2}\exp(x'\beta_\ell)} & \text{for } w=0 \\[2ex] \dfrac{\exp(x'\beta_w)}{1+\sum_{\ell=1}^{2}\exp(x'\beta_\ell)} & \text{for } w=1,2 \end{cases},$$

where we modified the notation that is used to denote the PS slightly to account for their dependence on the vector of unknown parameters $\beta = (\beta_1', \beta_2')'$. Usually, β is estimated by Maximum Likelihood (ML), thus optimizing the model's goodness of fit. ML maximization requires the following first-order conditions to be solved:

$$\frac{1}{N}\sum_{i=1}^{N}\sum_{w=0}^{2}\left[\frac{\mathbb{I}(W_{it}=w)}{p_w(X_{it-1};\beta)}\,\frac{\partial p_w(X_{it-1};\beta)}{\partial\beta'}\right]=0,$$

where N is the sample size. As pointed out by Imai and Ratkovic (2014), when a PS model is misspecified, MLE will provide biased estimates of the treatment effects. Instead of using a more flexible nonparametric approach, they proposed to robustify the parametric model by using a different estimation procedure, which exploits the covariate balancing property of PS—any function of the covariates is balanced across all treatment levels if weighted by the inverse of the PS. More formally,:

$$\mathrm{E}\left[\frac{\mathbb{I}(W_{it}=0)f(X_{it-1})}{p_0(X_{it-1})}\right]=\mathrm{E}\left[\frac{\mathbb{I}(W_{it}=1)f(X_{it-1})}{p_1(X_{it-1})}\right]=\mathrm{E}\left[\frac{\mathbb{I}(W_{it}=2)f(X_{it-1})}{p_2(X_{it-1})}\right].$$

where $f(\cdot)$ is a $(M\times 1)$ vector of functions, with $M \geq p$. These conditions can be used to set up a GMM estimator of β based on the following orthogonality conditions:[12]

$$\frac{1}{N}\sum_{i=1}^{N}\begin{bmatrix}\dfrac{\mathbb{I}(W_{it}=1)f(X_{it-1})}{p_1(X_{it-1})}-\dfrac{\mathbb{I}(W_{it}=0)f(X_{it-1})}{p_0(X_{it-1})}\\[2ex] \dfrac{\mathbb{I}(W_{it}=2)f(X_{it-1})}{p_2(X_{it-1})}-\dfrac{\mathbb{I}(W_{it}=0)f(X_{it-1})}{p_0(X_{it-1})}\end{bmatrix}=0 \qquad (5)$$

A natural choice is $f(X_{it-1}) = X_{it-1}$. The resulting estimator will provide robust PS

[12] In the binary treatment case, ML estimation is a special case of this approach. It corresponds to $f(X_{it-1}) = \partial p_1(X_{it-1})/\partial\beta$.

estimates that will improve covariate balancing across the treatment groups in respect of a misspecified ML estimation. It is also possible to overidentify the PS model by adding elements to $f(\cdot)$ in addition to X_{it-1}, such as squares or cross products of the elements of X_{it-1}.

3.4. Data and sample selection

Our data covers the 2001-2014 period and seven European countries (Austria, France, Germany, Italy, Netherlands, Spain, and Portugal), which represent some of the most established CB markets[13]. Many national CB regimes have deep roots, sometimes dating back to the 18^th century. Those regimes have recently been amended to account for financial innovation and the EU Capital Requirements Directive.

The data comes from multiple sources. Data on securitization was collected from AB-Alert, and data on CB issuance was collected from Bloomberg and the European Covered Bond Council (ECBC). Bank-level data was collected from Bankscope (Bureau van Dijk). Banks with missing information for total assets, loans, and net income were excluded from the sample. The initial dataset contained 5,493 banks, of which 5,304 never securitized or issued CBs during the sample period. Although all untreated banks could have been used to estimate PSs in principle, we opted to use just a subset — it is well known (see e.g. Cramer, 1999) that the estimation of multinomial probabilities becomes more difficult when the sample is highly unbalanced, that is, when one or more of the treatments is observed much more frequently than the others. Moreover, it is highly likely that the information loss that results from the exclusion of banks that are very different from the treated ones, in terms of the pretreatment covariates Xit1, from the control group is negligible (see Anderson, 1972). To operationalize this intuition, we cut the number of untreated banks from 5,304 to 311 by selecting those that were most similar to the observed treated banks. Specifically, for each bank i in one of the two treated groups, we looked for an untreated bank in the same country that had been observed in the same year and whose standardized pretreatment covariates were closest to those of bank i under the Euclidean norm. Treated banks for which no untreated banks in the same country or in the same year could be found were dropped. We repeated this procedure by looping over all treated banks several times, and we stopped when the number of observations in the control group was at least twice as large as the total number of observations in the treated groups. This preliminary step ensured that the control group would contain banks that are very similar, in terms of pretreatment covariates, to the treated banks, thus making it easier for the PS models to achieve the required covariate balancing across treatment levels.

Table 1 displays the frequencies of each treatment during the sample period[14]. From this table, it is evident that the issuance of asset-backed securities in Europe decreased after the financial crisis, while at the same time the issuance of CBs dramatically increased. The amount of securitized financial products issued in 2007 was 418 billion Euros, becoming 217 billion euros in 2012. Covered bonds issuance increased from 332 billion Euros to

[13]In some European countries, legislation on CBs was enacted at the beginning of 2000 (Finland in 2000; Ireland in 2001; Sweden in 2004; Portugal in 2006; Norway, Italy, and Greece in 2007; and the United Kingdom and the Netherlands in 2008).

[14]Even though our sample contains data from 2014, Table 1 stops at 2013 because observations from 2014 cannot be used in the outcome equations (4).

Table 1: Year Wise Treatment Frequencies

This table provides the observed number of securitizers and CB issuers over the sample period.

Year	Non-Issuers	Securitizers	CB Issuers	Total
2001	50	24	0	74
2002	54	23	1	78
2003	69	34	2	105
2004	70	28	6	104
2005	79	33	12	124
2006	97	46	17	160
2007	92	33	24	149
2008	81	18	22	121
2009	87	7	42	136
2010	93	8	45	146
2011	87	5	55	147
2012	102	6	70	178
2013	105	4	69	178
Total	1,066	269	365	1,700

403 billion Euros in the same period,[15] and decreased after 2012.

We follow previous studies (Aggarwal and Jacques, 2001; Casu et al., 2011; Salah and Fedhila, 2012) and use the changes in two different ratios as proxies for credit risk taking of banks, namely the Risk-Weighted Asset Ratio (RWATA) and the Loan Loss Provision Ratio (LLPR). RWATA captures a bank's allocation of assets across different risk categories and helps assess the quality of its asset portfolio[16] LLPR is a proxy of the quality of loans issued by banks: it shows how losses have been estimated by a bank on its loan portfolio. The higher is the LLPR ratio, the higher the issuance of risky assets by the bank. At the same time, this ratio is also indicative of a (conservative) risk averse approach of the bank. A positive relation of securitization with RWATA and a negative one with LLPR implies that banks take more risk and underprice this risk as a result of securitization, as explained by Kara et al. (2016).

[15] See the European Covered Bond Council

[16] The Basel Accord I divides the assets and off-balance-sheet activities of a bank into four categories as per their credit risk: *(i)* assets with zero risk weight (government securities and reserves, $AC\ I$); *(ii)* assets with a low risk (inter-bank deposits, $AC\ II$); *(iii)* assets with a medium level of risk (e.g. mortgage loans, $AC\ III$); *(iv)* assets with high default risk (e.g. consumer, commercial, and credit card loans, $AC\ IV$). The total risk-weighted assets of a bank are calculated as follows: $RWA = 0 \times AC\ I + 0.2 \times AC\ II + 0.5 \times AC\ III + 1.0 \times AC\ IV$, where AC = Asset Category. Under Basel II, which came into effect in 2008, the credit risk component can be calculated in two different ways, namely the standardized approach and the Internal Rating-Based Approach (IRB). The standardized approach is based on a revised and more specific asset class division of Risk-Weighted Assets (RWA). As most of the assets that are held by banks are not rated and fall in the fourth category, we can retain the same methodology to compute RWA. Due to the cost of implementing the IRBA, we conducted a random check and assumed that none of our banks had followed that methodology over the period under consideration.

4. Results and analysis

4.1. Descriptive analysis

Prior to describing the PS analysis, we report means and standard deviations for the pretreatment covariates across different treatment groups in Table 2. Our independent variables serve as proxies for the rationales of securitization and CB issuance that are cited in the literature, such as profitability, liquidity, and credit-risk management. The differences between securitizing and CB-issuing banks persist.

One popular view about securitization ties it to lax lending standards and a tendency to issue riskier loans. We find that securitizing banks, with a mean value of RWATA that is approximately 7% higher than that of CB-issuing banks, do tend to take more risks. We observed smaller differences for securitizing banks and for banks in the control group: our data shows that securitizing banks have an average RWATA that is only 2.2% higher than that of their non-securitizing counterparts, contrary to Bord and Santos (2015); Keys et al. (2012). CB issuing banks, conversely, take on less risk than the other two groups. These results can be ascribed to the incentives generated by *dual recourse*, that is, the right of bondholders to claim against the assets of the CB-issuing institution if it fails to reimburse them, and to the *dynamic covered pool* requirements, which oblige the credit institution that issues a bond to ringfence the covered pool and to ensure that the value of the assets that it contains is always at least equal to the value of the CBs. However, when we consider the other two measures of credit risk, LLPR and the Net Charge Off Ratio,[17] there are no significant differences between securitizing and CB-issuing banks but only between those banks and the control group. This provides evidence for the proposition that balance-sheet risk retention does not affect the risk attitude of banks and that both securitizing and CB-issuing banks have low-quality loans in their portfolios.

When we examined the loans, we found that the loan portfolios of securitizing banks differ both in their diversification and in their composition. Specifically, securitizers tended to hold a higher average share of residential mortgage loans in their portfolio than the control group (19% versus 15% for nonsecuritizers). Mortgage loans to households are an important business line for most European credit institutions, and they represent a sizeable proportion of some overall lending portfolios. The expansion of lending to this sector potentially creates collateral that the institutions in question can use to obtain medium- to long-term funding in a cost-efficient way. In the presence of a discrepancy between credit and deposit growth rates, banks have resorted to alternative funding sources. Indeed, banks have used securitization and CB issuance to finance their rapidly growing mortgage markets, and we detected only a small difference in the average residential and mortgage loan ratios between those groups. CB issuers appear to hold more consumer and retail loans instead (5% versus 3.7% for securitizers).

Securitizing banks, conversely, have a higher average loan-portfolio concentration than CB issuers, as shown by the Loan HHIs of 0.847 and 0.800, respectively. In other words, securitizing banks tend to be less diversified. Moreover, the significant difference in non-interest income ratios is consistent with securitizers having an additional source of income in the form of servicing fees because they play the role of originators, unlike CB issuers and banks that neither securitize nor issue CBs. This finding accords with Jiangli

[17]The Net Charge Off Ratio refers to the debt that is owed to a bank but is unlikely to be recovered.

Table 2: Summary statistics of sample banks' characteristics

Summary statistics of sample banks' characteristics for all banks, banks that neither securitize nor issue CB, securitizers only, and CB issuers only. The Loan HHI (Loan Hirschman-Herfindahl Index) is computed by using the shares of five types of loan (real estate, commercial and industrial, agricultural, consumer, and others) and measures the concentration of the loan portfolio of a bank. The interest and dividend income ratio is the ratio of interest and dividend income from securities to total interest income. It measures the return on investments that are different from the traditional sources of income for a bank (loans). The non-interest income ratio is measured as non-interest income divided by net operating revenue. It gauges the overall diversification status of a bank. A low ratio indicates that a bank is still focused on traditional source of income (i.e., interest). Size is measured by total assets in billion USD. Reputation is measured as the ratio of letters of guarantee to total assets.

	All banks		None		All Securitizers		CB Issuers	
Variable	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Risk-Weighted Asset Ratio	0.567	0.227	0.571	0.226	0.584	0.234	0.545	0.226
Loan Loss Provision Ratio	0.006	0.010	0.006	0.009	0.006	0.007	0.006	0.013
Net Charge-Off Ratio	0.001	0.005	0.000	0.006	0.001	0.004	0.001	0.005
Resid. Mortg. Loans Ratio	0.166	0.268	0.154	0.250	0.190	0.306	0.181	0.286
Corp & Comm. Loans Ratio	0.167	0.294	0.164	0.301	0.173	0.302	0.169	0.268
Cons. & Retail Loans Ratio	0.038	0.131	0.035	0.121	0.037	0.133	0.050	0.154
Loans HHI	0.805	0.351	0.800	0.321	0.847	0.367	0.789	0.417
Int. & Div. Income Ratio	1.005	0.126	1.013	0.084	0.998	0.192	0.986	0.159
Non-Int Income Ratio	0.306	0.585	0.308	0.361	0.417	1.246	0.219	0.236
Return on Assets	0.003	0.009	0.003	0.008	0.006	0.012	0.001	0.008
Return on Equity	0.031	0.337	0.026	0.393	0.077	0.163	0.010	0.238
Net Interest Margin	0.016	0.012	0.017	0.009	0.020	0.020	0.011	0.007
Equity Ratio	0.059	0.035	0.062	0.033	0.064	0.046	0.048	0.031
Size	122.006	282.384	83.786	220.140	154.278	335.531	209.845	367.059
Asset Growth	0.056	0.181	0.057	0.187	0.117	0.198	0.010	0.126
Reputation	0.055	0.112	0.048	0.070	0.089	0.216	0.049	0.095

and Pritsker (2008).

Turning to profitability measures, the data shows that securitizing banks are the most profitable in terms of return on assets, return on equity, and net interest margin. CB issuers are the least profitable group and have the lowest equity ratios. Table 2 shows that securitizers have a higher equity ratio than CB issuers, suggesting that securitizing banks, which enjoy superior access to external funding, do not hold less capital. This finding is in line with Martín-Oliver and Saurina (2007) but contradicts other studies (Ambrose et al., 2005, for example).

The final part of Table 2 emphasizes that securitized products and CBs are generally issued by larger banks. This finding is consistent with previous research that has found that larger banks are more likely to securitize (Uzun and Webb, 2007; Bannier and Hänsel, 2008; Jiangli and Pritsker, 2008; Minton et al., 2004, 2009). The mean value of total assets for securitizers and CB issuers is 84 and 154 percent larger than the control group, respectively. They also experience higher growth in their assets. Finally, securitizing banks have a higher ratio of letters of guarantee/total assets, which is considered as a proxy for a bank's reputation. This suggests that bigger and more reputable banks are involved in the issuance of securitized products. Our results are in line with the findings of previous studies (see for example Casu et al., 2011)

4.2. CBPS estimation of the PS model

Table 3 illustrates the parameter estimates of the multinomial logit model used to estimate the propensity score provided by exactly identified CBPS, that is, by GMM estimation based on the moment conditions (5) with $f(X_{it-1}) = X_{it-1}$. To avoid working with explanatory variables that could be affected by the treatment, we lagged them by one period. Furthermore, given that securitization and the issuance of CBs are governed by different national frameworks and that institutional settings, market characteristics, and legal systems vary across Europe, we used country fixed effects in all our models. Finally, in addition to year-specific fixed effects, we accounted for the varying effects of each independent variable before and after the 2008 financial crisis by interacting them with a financial-crisis dummy that is equal to 1 after 2008 and equal to 0 otherwise. Interestingly, the results suggest that banks securitized or issued CBs for similar reasons before and after the GFC.

Our independent variables are proxies for most of the commonly cited reasons for securitization and issuing CBs. To reflect the credit-risk management hypothesis and the need for liquidity that it posits, we used the LLPR and the net charge-off ratio (Calomiris and Mason, 2004; Jiangli and Pritsker, 2008; Minton et al., 2009; Affinito and Tagliaferri, 2010; Cardone-Riportella et al., 2010). As in Casu et al. (2013), , we controlled for bank profitability by using return on equity and return on assets (Minton et al., 2004; Bannier and Hänsel, 2008; Minton et al., 2009). Finally, we captured the portfolio diversification motive and the activity diversification motive by controlling for the loan HHI index and the non-interest income ratio (Affinito and Tagliaferri, 2010). Bank size captures the possible influence of economies of scale (Uzun and Webb, 2007; Bannier and Hänsel, 2008; Jiangli and Pritsker, 2008; Minton et al., 2009; Cardone-Riportella et al., 2010). We also captured other possible motives for securitization, such as expansion and reputation, by controlling for asset growth and the ratio of letters of guarantee to total assets.

Table 3 shows that asset growth is a significant determinant of securitization and covered bonds issuance. The same is not true for bank size. The different composition

Table 3: Exactly identified GMM-CBPS estimates of the multinomial logit Propensity Score model

This table provides exactly identified GMM-CBPS estimates of the multinomial logit Propensity Score model. Asymptotic standard errors in parenthesis. The model includes both year and country fixed effects.

	CB		SEC	
Intercept	-13.029	(73.598)	15.509	(54.087)
Loan Loss Provision Ratio$_{t-1}$	-25.817^{***}	(2.600)	-60.007^{***}	(2.271)
Net Charge-Off Ratio$_{t-1}$	94.754^{***}	(3.081)	79.845^{***}	(2.961)
Return on Assets$_{t-1}$	-231718^{***}	(2.029)	-259362^{***}	(1.553)
Return on Equity$_{t-1}$	14.736^{**}	(6.943)	16.151^{**}	(6.283)
Net Interest Margin$_{t-1}$	93.397^{***}	(3.675)	75.498^{***}	(2.942)
Equity Ratio$_{t-1}$	57.929^{***}	(6.161)	57.829^{***}	(6.036)
Resid. Mortg. Loans Ratio$_{t-1}$	0.275	(3.320)	-0.102	(3.086)
Corp & Comm. Loans Ratio$_{t-1}$	1.711	(7.990)	2.820	(7.897)
Cons. & Retail Loans Ratio$_{t-1}$	-3.906	(12.005)	-5.212	(11.911)
Loans HHI$_{t-1}$	-0.022	(5.885)	-0.844	(4.405)
Int. & Div. Income Ratio$_{t-1}$	3.320	(9.122)	3.738	(7.353)
Non-Int Income Ratio$_{t-1}$	-0.623	(4.093)	0.141	(4.030)
Size$_{t-1}$	0.602	(1.922)	0.212	(1.096)
Asset Growth$_{t-1}$	3.409^{***}	(0.868)	1.840^{**}	(0.729)
Reputation$_{t-1}$	-0.881	(4.160)	-2.544	(3.851)
FC$_t$ × Loan Loss Provision Ratio$_{t-1}$	57.751^{***}	(0.597)	113.463^{***}	(0.471)
FC$_t$ × Net Charge-Off Ratio$_{t-1}$	-43.748^{***}	(2.236)	-22.298^{***}	(2.142)
FC$_t$ × Return on Assets$_{t-1}$	175.417^{***}	(0.684)	317.148^{***}	(0.481)
FC$_t$ × Return on Equity$_{t-1}$	-13.608^{*}	(7.470)	-14.867^{**}	(7.210)
FC$_t$ × Net Interest Margin$_{t-1}$	101.066^{***}	(6.599)	-24.926^{***}	(6.318)
FC$_t$ × Equity Ratio$_{t-1}$	-68.437^{***}	(8.083)	-72.972^{***}	(7.892)
FC$_t$ × Resid. Mortg. Loans Ratio$_{t-1}$	-5.061^{**}	(2.313)	-2.273	(2.144)
FC$_t$ × Corp & Comm. Loans Ratio$_{t-1}$	0.023	(6.507)	-2.927	(6.197)
FC$_t$ × Cons. & Retail Loans Ratio$_{t-1}$	6.101	(12.797)	6.645	(12.252)
FC$_t$ × Loans HHI$_{t-1}$	0.098	(8.867)	0.633	(8.317)
FC$_t$ × Int. & Div. Income Ratio$_{t-1}$	12.898^{**}	(5.125)	-0.201	(1.007)
FC$_t$ × Non-Int Income Ratio$_{t-1}$	1.248	(8.676)	0.095	(8.456)
FC$_t$ × Size$_{t-1}$	-1.302	(16.553)	-1.054	(6.956)
FC$_t$ × Asset Growth$_{t-1}$	3.309	(2.069)	0.840	(1.728)
FC$_t$ × Reputation$_{t-1}$	5.442^{***}	(1.805)	4.460^{***}	(1.084)
Observations	1700			
Log-Likelihood	-1304.652			

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

of bank loans did not affect the choice between securitizing or issuing CBs before and after the 2008 crisis. Only after the 2008 crisis did banks with a higher proportion of residential and mortgage loans issue fewer CBs, while the effect on securitization is statistically insignificant. Therefore, our results do not support the conclusions of Kara et al. (2016) who found that loans with a higher default risk have a lower probability of being securitized.

Instead, banks with a higher net charge-off ratio, that is, with a higher share of bad debts, tended to issue CBs or to securitize. This tendency was more pronounced before the crisis than after it. The Net Charge-Off Ratio is an ex post measure of loss that reflects losses on loans made in the past that require financing . The decrease in the absolute value of the coefficient after 2008 suggests that the regulatory changes that followed the crisis limited the ability of the banks that had incurred large losses to securitize or issue CBs. This said, the coefficient for LLPR was negative and significant before the financial crisis but reverted to positive thereafter, showing that banks that had already set aside a provision to cover different kinds of potential losses on loans (which could have stemmed from nonperforming loans, customer bankruptcy, and credit renegotiations) were less likely to securitize or issue CBs before the GFC. Overall, our evidence supports the proposition that securitization and CB issuance mainly provide banks with new sources of financing. More profitable banks, as indicated by Return on Equity (ROE), had a higher probability of securitizing or issuing CBs. The implication is that profitability is not a determinant of securitization and CB issuance. After 2008, the effect of profitability on securitization and CB issuance was dampened, and the coefficient of CB becomes very close to 0 in that period. Conversely, banks whose return on assets was lower, that is, whose indebtedness for a given level of equity was higher, had a higher probability of issuing CBs or securitizing. At the same time, banks with higher net interest margins had a higher probability of securitizing during the whole period under observation. This suggests the possibility that securitizing banks tend to reduce their reliance on interest income.

In general, when we interact the independent variables with the FC dummy, we find that the coefficients decrease in absolute value. Usually, their signs change after 2008, that is the probability of securitizing and issuing CBs is positively related to LLPR, which suggests that the need for liquidity becomes more pronounced after an increase in the implicit loan-loss provisions of banks. Finally, the positive coefficient of the equity ratio shows that banks were not using securitization for capital arbitrage before the GFC. This said, the sign changes after the crisis. These results are in line with Cardone-Riportella et al. (2010) and Martín-Oliver and Saurina (2007), but contradict other studies (see e.g. Ambrose et al., 2005; Acharya et al., 2013).

We now assess the performance of the estimated PS model in terms of its ability to balance the distribution of pretreatment covariates across treatment groups. Table 4 reports the results of two-sample t-tests by presenting a pairwise comparison of the means of the covariates in the three groups before and after weighting by the inverse PS that is estimated by an exactly identified CBPS. In all columns, we use asterisks to denote statistical significance. Table 4 shows that before weighting, the means of several pretreatment covariates differ significantly across treatment groups. Therefore, even when we only include the untreated banks which are closest (under the Euclidean norm of the standardized pretreatment covariates) to the treated banks (following the procedure described in Section 3.4) in the control group, the three groups are still systematically different in several aspects. A comparison of the unweighted outcome variables across groups would yield severely biased estimates of the effect of securitization and CB issuance on the risk-taking behavior of banks. After weighting, however, the means across groups are much closer, and all statistically significant discrepancies are eliminated. Thus, we conclude that our PS estimates are effective in rebalancing the distribution of the pretreatment covariates across the groups.

Table 4: t-test for equality of means of pretreatment covariates before and after weighting

This table compares the means of the pretreatment covariates of banks belonging to different treatment groups using *paired-sample t-test*. The Null hypothesis is: *Means are equal across treatment groups.* Columns (1)-(3) contain differences in unweighted sample averages; columns (4)-(6) contain differences in sample averages weighted by the inverse of the multinomial logit propensity scores estimated by exactly identified GMM-CBPS. The loan Hirschman-Herfindahl index (Loan HHI) is computed using five loans shares (real estate, commercial and industrial, agricultural, consumer, and other loans) and measures the concentration of the loan portfolio of a bank. The interest and dividend income ratio is the ratio of interest and dividend income from securities to total interest income., and it measures the return from investments different from the traditional income sources of a bank (loans). The non-interest income ratio is given by non-interest income divided by net operating revenue. It gauges the overall diversification status of a bank. A low ratio indicates that a bank is still focused on the traditional source of income (i.e., interest income). Size is measured as the natural log of total assets. Reputation is measured as a ratio of the letter of guarantee to total assets.

	Original sample			Weighted sample		
	(1) SEC-None	(2) CB-None	(3) SEC-CB	(4) SEC-None	(5) CB-None	(6) SEC-CB
Loan Loss Provision Ratio	0.000	0.001	0.000	0.001	0.000	0.001
Net Charge-Off Ratio	0.001**	0.001***	0.000	0.000	0.000	0.000
Resid. Mortg. Loans Ratio	0.046**	0.000	0.046*	−0.016	−0.015	−0.001
Corp & Comm. Loans Ratio	0.015	−0.016	0.031	0.006	0.011	−0.004
Cons. & Retail Loans Ratio	0.006	0.014*	−0.008	0.003	0.004	−0.002
Loan HHI	0.056**	0.021	0.035	0.032	0.023	0.010
Int. & Div. Income Ratio	−0.018	−0.036***	0.018	−0.003	−0.003	0.000
Non-Int Income Ratio	0.109***	−0.118***	0.227***	0.027	−0.013	0.040
Return on Assets	0.003***	−0.002***	0.005***	0.000	0.000	0.001
Return on Equity	0.035***	−0.048***	0.083***	−0.001	−0.007	0.005
Net Interest Margin	0.003**	−0.006***	0.009***	0.000	−0.002	0.002
Equity Ratio	0.004	−0.013***	0.018***	−0.001	−0.006	0.005
Size	0.521***	1.419***	−0.898***	0.214	0.305	−0.092
Asset Growth	0.043***	−0.038***	0.080***	0.014	−0.003	0.017
Reputation	0.043***	0.010	0.033**	0.015	0.010	0.005

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.3. *Estimation of treatment effects*

We now turn to inquire whether securitization and CB issuance affect the risk-taking behavior of issuing banks. We estimate these treatment effects by using the DR estimator that we described in Section 3.2, which amounts to applying weighted least square (WLS), with weights given by the inverse of the PSs that were estimated through GMM-CBPS, to linear regression models in which an outcome variable is explained by treatment dummies and pretreatment covariates. We consider the change of two measures of bank performance (before and after the treatment period) as outcome variables: (*i*) RWATA, and (*ii*) LLPR. In particular, we consider the change in these two variables over a two-year and a four-year window to measure the corresponding effects in the short and in the long run. The results are reported in Table 5 and Table 6. All the models control for country-specific fixed effects, but we also consider a specification that controls for year-specific effects.

Table 5 5 shows that, in the short run and under all specifications, securitization and CB issuance did not affect the risk-weighted assets of banks before the GFC. This runs

Table 5: Average Treatment Effect Estimates - Short Run

This table provides the Doubly Robust-Inverse Probability Weighted Least Squares estimates of the Average Treatment Effect over the two-year interval $(t-1, t+1)$, where t denotes the bank-specific year the treatment took place. Weights are estimated inverse PS from the exactly identified CBPSs model. The outcome variables are $\text{RWATA}_{it+1} - \text{RWATA}_{it-1}$ and $\text{LLPR}_{it+1} - \text{LLPR}_{it-1}$. The models in columns 1 and 4 use as explanatory variables the securitization and CB issuance indicators at time t, the financial crisis dummy and the interaction terms of securitization and CB issuance with the financial crisis dummy. Columns 2 and 5 add pretreatment bank-specific control variables at $t-1$, and Columns 3 and 6 also include time fixed effects. Country fixed effects are included in all models.

	$\text{RWATA}_{it+1} - \text{RWATA}_{it-1}$			$\text{LLPR}_{it+1} - \text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.047**	−0.169*	−0.164	−0.005**	−0.044***	−0.047***
	(0.021)	(0.102)	(0.104)	(0.002)	(0.011)	(0.011)
$\text{Securitization}_{it}$	−0.004	0.007	0.009	0.002	0.002	0.002
	(0.020)	(0.020)	(0.020)	(0.002)	(0.002)	(0.002)
CB Issuance_{it}	−0.032	0.009	0.005	−0.015***	−0.016***	−0.016***
	(0.024)	(0.024)	(0.024)	(0.003)	(0.003)	(0.003)
Financial Crisis	−0.017	−0.010		0.005**	0.004*	
	(0.019)	(0.019)		(0.002)	(0.002)	
FC × $\text{Securitization}_{it}$	−0.110***	−0.125***	−0.135***	−0.004	−0.006**	−0.005*
	(0.026)	(0.026)	(0.026)	(0.003)	(0.003)	(0.003)
FC × CB Issuance_{it}	0.046	−0.020	−0.015	0.011***	0.013***	0.012***
	(0.030)	(0.029)	(0.030)	(0.003)	(0.003)	(0.003)
$\text{Loan Loss Provision Ratio}_{it-1}$		6.063***	6.205***		−0.305***	−0.273**
		(1.011)	(1.033)		(0.108)	(0.110)
$\text{Net Charge-Off Ratio}_{it-1}$		−0.580	−0.841		−0.559***	−0.466***
		(1.346)	(1.382)		(0.144)	(0.147)
$\text{Return on Assets}_{it-1}$		−3.654***	−3.603**		0.279*	0.176
		(1.373)	(1.398)		(0.147)	(0.148)
$\text{Return on Equity}_{it-1}$		0.141***	0.141***		0.008*	0.007
		(0.039)	(0.039)		(0.004)	(0.004)
$\text{Net Interest Margin}_{it-1}$		0.009	−0.105		0.143**	0.198***
		(0.639)	(0.658)		(0.068)	(0.070)
$\text{Equity Ratio}_{it-1}$		0.884***	0.882***		−0.098***	−0.088***
		(0.200)	(0.200)		(0.021)	(0.021)
$\text{Resid. Mortg. Loans Ratio}_{it-1}$		0.042*	0.040*		−0.007***	−0.007***
		(0.024)	(0.024)		(0.003)	(0.003)
$\text{Corp \& Comm. Loans Ratio}_{it-1}$		0.064***	0.069***		−0.008***	−0.006***
		(0.019)	(0.019)		(0.002)	(0.002)
$\text{Cons. \& Retail Loans Ratio}_{it-1}$		−0.129***	−0.129***		0.005	−0.001
		(0.045)	(0.046)		(0.005)	(0.005)
Loans HHI_{it-1}		−0.135***	−0.141***		0.003*	0.002
		(0.015)	(0.015)		(0.002)	(0.002)
$\text{Int. \& Div. Income Ratio}_{it-1}$		−0.006	−0.011		0.005	0.007
		(0.053)	(0.053)		(0.006)	(0.006)
$\text{Non-Int Income Ratio}_{it-1}$		0.019	0.034		−0.009***	−0.008***
		(0.023)	(0.023)		(0.002)	(0.002)
Size_{it-1}		0.009***	0.009***		0.002***	0.002***
		(0.003)	(0.003)		(0.0003)	(0.0003)
$\text{Asset Growth}_{it-1}$		0.061*	0.067**		−0.030***	−0.031***
		(0.032)	(0.033)		(0.003)	(0.003)
Reputation_{it-1}		0.024	0.011		0.016***	0.016***
		(0.042)	(0.042)		(0.004)	(0.004)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,700	1,700	1,700	1,700	1,700	1,700
R^2	0.066	0.153	0.182	0.062	0.207	0.242
Adjusted R^2	0.060	0.140	0.164	0.056	0.195	0.225
Residual Std. Error	0.153	0.147	0.145	0.017	0.016	0.015
F Statistic	10.795***	11.664***	9.979***	10.078***	16.785***	14.532***

*$p<0.1$; **$p<0.05$; ***$p<0.01$

contrary to the finding of Casu et al. (2011). After the GFC, securitizers exhibited a decrease in RWATA, a result that suggests that the risk-taking behavior of banks changed. The riskiness of the portfolios of CB-issuing banks did not change in the short run, neither before the financial crisis nor after it. Accordingly, our data do not support the hypothesis that on-balance-sheet risk retention decreases the risk appetite of banks.

In columns 2 and 3, we add controls for the share of risky loans at a bank at t 1. Banks that held a high proportion of consumer and retail loans in their portfolios are associated with a decrease in the level of risky assets; the opposite is true of banks with high shares of residential and mortgage loans. Owing to their intrinsically riskier nature, consumer loans tend to show higher impairment rates than mortgage loans. Interestingly, a higher pretreatment level of LLPR and profitability (return on equity) and a lower level of return on assets are associated with an increase in risk taking. Similarly, the coefficient for the equity ratio is positive and statistically significant, a result that casts doubt on the view that poorly capitalized banks issue risky assets. Capital can be considered as a "buffer of uninsured private funds to absorb portfolio losses" Avery and Berger (1991). Finally, the positive and significant coefficient for size shows that larger banks do take more risks.

Columns 4 to 6 illustrate the results from estimating the same models by using the change in LLPR, $\text{LLPR}_{(t+1)} - \text{LLPR}_{(t-1)}$, as an outcome variable. The estimates for the securitization dummy coefficients are still statistically insignificant, whereas those for the CB indicator are negative, reflecting the diminished need to set aside capital to cover expected losses at CB-issuing banks. The coefficient for the interaction term with the financial-crisis dummy and CB issuance is positive, but the total effect remains negative, albeit close to 0. This suggests that after the financial crisis, regulation forced CB-issuing banks to increase loan-loss provisions. These results may allay the concern that banks might have underestimated their risk levels after the financial crisis. The positive and significant coefficient for size shows that large banks that take more risks also increase their LLPR.

Table 6 provides the results from the same analysis of the changes in RWATA and LLPR over a four-year interval. The treatment occurs in the second year. The analysis aims to measure the effects of securitization and the issuance of CB on risk-taking behavior over the long run. Similar to the short-run results discussed above, in the long run, the effects of securitization and the issuance of CBs are not statistically significant. Moreover, no significant change in this pattern can be observed after the financial crisis. The evidence for securitizing and CBs issuing banks is similar to the one observed in the short run. The only difference is that in the long run, banks that issue commercial loans decrease the riskiness of their portfolios. Many other significant effects disappear when we consider the change in LLPR. To determine whether the effect may be attributed to the change in the risk attitudes of banks after the financial crisis, we estimated the same specifications separately before and after 2008. The results are provided in Appendix B and are discussed in the next section.

The last three columns in Table 6 show the results for $\text{LLPR}_{it+3} - \text{LLPR}_{it-1}$. In this case, the coefficients of the securitization and CB indicators are statistically insignificant before and after the 2008 financial crisis. Since the riskiness of bank portfolios does not change in the long run, we treat this result as evidence that banks are not underpricing risk.

Table 6: Average Treatment Effect Estimates - Long Run

This table provides the Doubly Robust-Inverse Probability Weighted Least Squares estimates of the Average Treatment Effect over the four-year interval $(t_{i-1} - t_{i+3})$, where t_i denotes the year the treatment took place. Weights are inverse Propensity Scores from the exactly identified CBPSs model. The outcome variables are $\text{RWATA}_{it+3} - \text{RWATA}_{it-1}$ and $\text{LLPR}_{it+3} - \text{LLPR}_{it-1}$. The models in columns 1 and 4 use as rhs variables the securitization and CB issuance indicators at time t_i, the financial crisis dummy and the interaction terms of securitization and CB issuance with the financial crisis dummy. Columns 2 and 5 add pretreatment bank-specific control variables at $t_i - 1$, and Columns 3 and 6 also include time fixed effects. Country fixed effects are included in all models.

	$\text{RWATA}_{it+3} - \text{RWATA}_{it-1}$			$\text{LLPR}_{it+3} - \text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.094***	0.356***	0.268***	0.006	0.009	0.010
	(0.019)	(0.091)	(0.093)	(0.008)	(0.045)	(0.046)
$\text{Securitization}_{it_i}$	−0.038**	−0.016	−0.012	−0.006	−0.007	−0.008
	(0.017)	(0.016)	(0.016)	(0.008)	(0.008)	(0.008)
$\text{CB Issuance}_{it_i}$	0.006	0.019	0.027	−0.005	−0.009	−0.013
	(0.020)	(0.019)	(0.019)	(0.009)	(0.009)	(0.010)
$\text{Financial Crisis}_{t_i}$	−0.078***	−0.067***		−0.007	−0.008	
	(0.018)	(0.017)		(0.008)	(0.008)	
$\text{FC} \times \text{Securitization}_{it_i}$	0.043*	0.025	0.017	0.006	0.006	0.008
	(0.025)	(0.022)	(0.023)	(0.011)	(0.011)	(0.011)
$\text{FC} \times \text{CB Issuance}_{it_i}$	0.012	−0.032	−0.038	0.007	0.012	0.016
	(0.028)	(0.025)	(0.026)	(0.012)	(0.012)	(0.013)
$\text{Loan Loss Provision Ratio}_{it_i-1}$		4.684***	4.425***		−1.146**	−1.122**
		(1.069)	(1.081)		(0.528)	(0.538)
$\text{Net Charge-Off Ratio}_{it_i-1}$		−2.738*	−2.432*		−0.360	−0.554
		(1.451)	(1.476)		(0.717)	(0.734)
$\text{Return on Assets}_{it_i-1}$		−2.404*	−3.189**		−0.004	0.072
		(1.418)	(1.452)		(0.700)	(0.723)
$\text{Return on Equity}_{it_i-1}$		0.097***	0.093***		−0.004	−0.0001
		(0.035)	(0.035)		(0.018)	(0.018)
$\text{Net Interest Margin}_{it_i-1}$		−1.484***	−1.344**		−0.135	−0.154
		(0.545)	(0.566)		(0.269)	(0.282)
$\text{Equity Ratio}_{it_i-1}$		1.157***	1.248***		0.018	−0.004
		(0.192)	(0.193)		(0.095)	(0.096)
$\text{Resid. Mortg. Loans Ratio}_{it_i-1}$		0.049**	0.042*		−0.003	−0.004
		(0.022)	(0.022)		(0.011)	(0.011)
$\text{Corp \& Comm. Loans Ratio}_{it_i-1}$		−0.049***	−0.043**		0.015*	0.014
		(0.017)	(0.017)		(0.008)	(0.009)
$\text{Cons. \& Retail Loans Ratio}_{it_i-1}$		−0.244***	−0.224***		0.006	−0.005
		(0.039)	(0.040)		(0.020)	(0.020)
$\text{Loans HHI}_{it_i-1}$		−0.185***	−0.194***		0.001	0.002
		(0.012)	(0.012)		(0.006)	(0.006)
$\text{Int. \& Div. Income Ratio}_{it_i-1}$		−0.110**	−0.101**		0.008	0.006
		(0.045)	(0.045)		(0.022)	(0.023)
$\text{Non-Int Income Ratio}_{it_i-1}$		0.004	0.013		0.002	−0.00003
		(0.019)	(0.020)		(0.009)	(0.010)
Size_{it_i-1}		−0.002	−0.001		−0.0002	−0.001
		(0.003)	(0.003)		(0.001)	(0.001)
$\text{Asset Growth}_{it_i-1}$		0.206***	0.222***		−0.017	−0.013
		(0.029)	(0.030)		(0.014)	(0.015)
$\text{Reputation}_{it_i-1}$		0.015	−0.0003		−0.011	−0.009
		(0.033)	(0.033)		(0.016)	(0.016)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,250	1,250	1,250	1,250	1,250	1,250
R^2	0.139	0.348	0.365	0.005	0.015	0.025
Adjusted R^2	0.132	0.334	0.346	−0.004	−0.006	−0.003
Residual Std. Error	0.126	0.111	0.110	0.055	0.055	0.055
F Statistic	18.196***	25.099***	19.898***	0.545	0.735	0.836

*$p<0.1$; **$p<0.05$; ***$p<0.01$

4.4. Robustness checks

To assess the robustness of the results that were presented in the previous section, we estimated the treatment equations and the PS model over different sample windows and using alternative econometric methodologies. This section presents the results of this analysis.

4.4.1. Separate pre- and post-financial crisis estimation

The full sample we have used so far includes observations for the period between 2001 and 2014. It should be noted that these dates refer to the years in which banks either securitized or issued CBs, denoted by t (which differs across banks). The pretreatment covariates refer to year $t-1$, aand the changes in the outcome variables RWATA and LLPR are measured over time intervals that start from $t-1$ and end at $t+1$ (short run effect) and $t+3$ (long run effect). Our first robustness check consists in assessing the extent to which our results are driven by the 2008 financial crisis. To this end, we estimated the treatment equations before and after the 2008 financial crisis separately, using the weighted least squares technique on the basis of the PS that we estimated by reference to an exactly identified CBPSs for the full sample. The two subsamples were chosen so that the observations would lie entirely on either side of 2008. For the precrisis period, we selected observations with a t between 2001 and 2006 for the short-run-effect equation and a t between 2001 and 2004 for the long-run one. For the post-crisis period, observations start in 2009 for both short- and long-run effects. This sampling strategy produces a clear separation between the two observation windows, and it rules out the possibility that the estimated treatment effects might be partially contaminated by the occurrence of the financial crisis. This gain comes at the price of a reduction in the number of available observations. The results are provided in Table B.1, Table B.2, Table B.3 and Table B.4 in Appendix B.

These tables show that before the financial crisis, the effect of securitization on the two outcomes was negligible in both the short and the long run. The effect of issuing CBs on the short run change in LLPR was statistically significant and negative. It was not significant anywhere else. After the financial crisis, past securitization had a significant negative effect on the change in RWATA and a significant positive effect on LLPR in the long run; all other effects were statistically negligible. These results mirror the ones that we obtained by estimating the treatment equations for the full sample. Understandably, the lower number of observations in the separate estimations generates noisier estimates, which, in turn, imply a lower number of statistically significant pretreatment covariates relative to the full- sample results. However, the signs of the significant estimates are consistent with those given in Table 5 and Table 6. Overall, the results from the separate subsamples cohere with the discussion of the full sample period in Section 4.3.

4.4.2. Overidentified CBPS

It is well known that the misspecification of a PS model can have large adverse consequences for the subsequent estimation of treatment effects. The analysis that was developed in the preceding sections used the DR treatment-effect estimator. For it to be valid, either the PS model or the treatment-effect equation must be specified correctly. For this reason, the technique is widely considered to be preferable to alternatives that are based on PS matching or simpler weighting schemes. It is still important, however, to check whether our main results change when the PSs are estimated by using a different technique or a different model specification.

A natural alternative to the exactly identified CBPS-GMM estimation method that we described in Section 4.2 is the overidentified CBPS-GMM system that combines the moment conditions that we have used so far with the loglikelihood score of the multinomial logit model, as suggested by Imai and Ratkovic (2014). Given K pretreatment covariates to balance across three groups that are identified by treatment level, this choice amounts to increasing the number of moment conditions from $2K$, the number of parameters in the multinomial logit model, to $4K$. The results that we obtained by estimating the multinomial logit model through the overidentified CBPSs method are given in Table B.5, Table B.6, Table B.7 and Table B.8 in Appendix B.

Table B.5 reports the parameter estimates, and Table B.6 compares the means of the pretreatment covariates across the three treatment groups, before and after weighting by the inverse PS that we estimated through the overidentified CBPSs, by reference to paired t-tests. If Table B.6 is compared with Table 4, it immediately becomes apparent that the inclusion of the additional moment conditions causes the balancing property of the estimated PS to deteriorate. The differences between means are uniformly smaller in the weighted data than they are in the original data, but, unlike in Table 4, a few differences are statistically different from 0 even after weighting. This illustrates the trade-off that inheres in the choice of estimation criterion, which is between fitting the data (the purpose of including the loglikelihood scores) and balancing the distribution of pretreatment covariates across treatment groups (the purpose of using moment conditions that impose equality between weighted averages across groups). The foregoing also confirms the correctness of our decision to use the exactly identified CBPSs approach as a preferred method for estimating the PS model.

Table B.7 and B.8 display the results that we obtained by estimating the short- and long-run-treatment equations by using the overidentified CBPSs, and they should be compared to Table 5 and Table 6. The discussion of Table B.6 above suggests that these estimates should be treated with caution—weighting by the inverse PS still leaves some statistically significant differences in the distributions of the pretreatment covariates across groups. This means that, even after weighting, banks in different groups differ systematically on some of these variables (such as, e.g., "Size," "Net Interest Margin," or "Equity Ratio"), which, in turn, complicates the interpretation of the estimated treatment effects. Still, the results show that the two sets of estimated PSs yield very similar estimates of the outcome equations. The signs and the statistical significance of the treatment effects are almost always very close, irrespective of the outcome variable, the treatment horizon, and the sample period (before or after the financial crisis). The same conclusion also holds for the estimated coefficients of the pretreatment covariates. The last two columns in Table B.6 show that this specific set of PSs cannot balance the means of the covariates of the CB-issuer group and those of the other groups. Therefore, it is not surprising that the only discrepancies in the outcome equations are in the short-run effects of CB issuance in the LLPR equation.

4.4.3. Generalized Boosted Models (GBM)

The GBM approach estimates a nonparametric and piecewise constant yet highly flexible model for the PS $p_w(X_{it})$. The final PS estimate is obtained by combining estimates that are generated by classification trees that are grown sequentially, whereby each tree is trained on a version of the original data set that is modified to account for the quality of the fit obtained by previous trees. Although the individual trees are simple, the method gradually creates a flexible piecewise-constant approximating function for the conditional treatment probabilities. McCaffrey et al. (2004) adapted the general GBM model-building procedure to PS estimation by allowing the complexity of the model to be determined by the optimization of the covariate balancing between the inverse-probability-weighted treatment and the control samples. Unlike the CBPSs, GBM does not necessitate the adoption of a functional-form assumption about $p_w(X_{it})$, and can, in principle, allow arbitrary nonlinearities in the true PS. It can also scale fairly well with the number of covariates, all while keeping the PS estimates stable over their support.

Table B.9, Table B.10 and Table B.11 contain the results that we obtained from using the GBM approach to estimate the PSs and describe their application to the estimation of the treatment equations. Table B.9 illustrates the results of the paired t-tests that check whether weighting the pretreatment variables by the inverse of the PS that is estimated by GBM effectively removes all differences across treatment groups. Unlike the results for the exactly identified CBPSs that are presented in Table 4, and similar to overidentified CBPSs (see Table B.6), weighting by GBM estimated PS reduces the absolute size of the differences in means. However, some of them remain statistically significant. Like in Table B.6, this effect is especially pronounced among the group of CB-issuing banks, for which several pretreatment covariates (e.g., "Net Interest Margin," "Equity Ratio," "Size," and "Asset Growth") are characterized by mean values that remain significantly different from those that prevail in the other two groups, even after weighting. As for the results described in the previous section, we should emphasize that these differences cast some doubts on the validity of the treatment-effect estimates that we obtained by using this weighting scheme.

Despite these caveats, our main results are generally confirmed, even in this case. In the short run, we again detected a negative effect of past securitization on the change in RWATA after the financial crisis as well as a negative effect of CB issuance on the change in LLPR before the crisis. Contrary to the estimates reported in Table 5, past CB issuance has no effect on the latter outcome. The signs of the effects and of the coefficients of most pretreatment covariates are coherent with our main results, but their size is generally reduced, which may imply a loss of significance. In the long run, neither treatment has any effect on the outcome variables, as in Table 6.

5. Discussion and conclusion

We investigated the impact of securitization and CB issuance on the credit-risk-taking behavior of European banks in the period between 2001 and 2014, that is, before and after the 2008 GFC. In particular, we strove to understand whether CB-issuing banks are less inclined to assume credit risk because they retain most of it on their balance sheets, as suggested by recent studies. Those studies also indicate that securitizing banks tend to issue more risky assets. We move from Casu et al. (2011) who used precrisis data from securitizing U.S. commercial banks and found a negative correlation between securitization and RWATA in the short run and no significant correlation between the two variables in the long run. Their empirical results suggest that banks that hold more securitized assets are more risk averse and that the negative relationship between securitization and risk taking is driven primarily by the securitization of mortgages, home equity lines of credit, and other consumer loans. Our paper departed from the literature, in that it focused on seven major European countries with CB markets that are more developed than the U.S. one. This allowed us to include the risk-taking behavior of CB-issuing banks in the analysis. We also addressed self-selection concerns about the endogeneity of the decision to securitize or issue CBs by using the CBPSs method. It is considered to be more robust than traditional PS-based methods because it improves covariate balancing across treatment groups. We provided evidence that the absence of skin in the game, that is, on-balance-sheet risk retention, is not what drives securitizing banks to take risks. This was true even before the 2008 financial crisis. Furthermore, we showed that European banks did not use securitization to transfer credit risk. Indeed, if our findings are correct, it was only after the crisis that securitizers began to exhibit decreases in their RWATA, which suggests a change in risk taking behavior. More precisely, banks that issue CBs did not change the risk levels of their portfolios in the short run, either before the financial crisis or after it. Therefore, our data do not support the hypothesis that on-balance-sheet risk retention decreases the risk appetite of banks. Additionally, the different compositions of bank loans did not affect the choice between securitizing and issuing CBs before and after the 2008 crisis. Only after the crisis did banks with a higher proportion of residential and mortgage loans issue fewer CBs; the effect on securitization is statistically insignificant. Accordingly, our results do not support the conclusions of Kara et al. (2016), who found that loans with a higher default risk have a lower probability of being securitized. Overall, our evidence suggests that European banks use securitization and CBs for the same reasons, that is, to acquire funding, and not to manage risk. Our results are probably related to the different statutory and regulatory frameworks in Europe, under which collateral valuation processes and issuer risk-management policies are subject to more stringent quality standards (Surti, 2010)).

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Appendix A. Pretreatment covariates

Table A.1: Pretreatment covariates

AcroFnym	Variable Name	Description
	Credit Risk Measures	
RWATA	RWATA Ratio	Risk-weighted assets / Total Assets
LLPR	Loan Loss Provision Ratio	Provision for loan losses / Total Loans
NCOR	Net Charge-Off Ratio	Net Charge-Offs / Total Loans
	Profitability	
ROE	Return on Equity	Net Income / Total Equity
ROA	Return on Assets	Net Income / Total Assets
NIM	Net Interest Margin	Net Interest Income / Total Assets
	Liquidity	
LiqR	Liquidity Ratio	Cash + Securities / Total Assets

Continued on next page

Table A.1 – continued from previous page

Acronym	Variable Name	Description
	Capital Ratios	
ER	Equity Ratio	Total Equity / Total Assets
	Loan Portfolio	
RMLR	Residential and Mortgage Loans Ratio	Residential and Mortgage Loans / Total Loans
CCLR	Corporate and Commercial Loan Ratio	Corporate and Commercial Loans / Total Loans
CRLR	Consumer & Retail Loans Ratio	Consumer Loans / Total Loans
LHHI	Loan HHI	$\text{RMLR}^2 + \text{CCLR}^2 + \text{CRLR}^2 + \text{OLR}^2$
	Income Structure	
IDIS	Interest and Dividend Income Ratio	Interest and Dividend Income on Securities / Total Interest Income
NINOR	Non Interest Income Ratio	Non-Interest Income / Net Operating Revenue
	Balance Sheet Structure	
Size	Size of Bank	Log(Total Assets)
LR	Loan Ratio	Loans / Total Assets
AG	Asset Growth	Asset_t - Assets_{t-1} /Assets_t
Rep	Reputation of Bank	Guarantees / Total Assets

Appendix B. Robustness Check

This Appendix contains several Tables illustrating the results obtained in estimating the PS model and the treatment effect regressions over different observation windows or using alternative econometric methodologies. For a discussion, see the comments in section 4.4.

Table B.1: Average Treatment Effect Estimated through CBPS - Pre Crisis Short Run

This table provides the results of the Average Treatment Effect estimated by Weighted Least Square (WLS) for the short run during the pre-crisis period 2001-2006. Weights are the inverse of the Propensity Scores estimated by exactly identified CBPS over the full sample. Three models were estimated for two outcome variables, $\text{RWATA}_{it+1} - \text{RWATA}_{it-1}$ and $\text{LLPR}_{it+1} - \text{LLPR}_{it-1}$. The results in columns 1 and 4 include securitization and CB Issuance at time t only. Columns 2 and 5 control for bank specific pretreatment variables at $t-1$, and Columns 3 and 6 include the year effect. Country fixed effects are included in all columns.

	$\text{RWATA}_{it+1} - \text{RWATA}_{it-1}$			$\text{LLPR}_{it+1} - \text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.013	0.185^{*}	0.209^{**}	-0.019^{***}	-0.070^{***}	-0.072^{***}
	(0.021)	(0.105)	(0.106)	(0.003)	(0.012)	(0.012)
$\text{Securitization}_{it}$	−0.003	0.003	0.003	0.001	0.002	0.002
	(0.013)	(0.013)	(0.013)	(0.002)	(0.001)	(0.001)
CB Issuance_{it}	−0.008	−0.013	−0.016	-0.006^{***}	-0.009^{***}	-0.009^{***}
	(0.017)	(0.017)	(0.017)	(0.002)	(0.002)	(0.002)
$\text{Loan Loss Provision Ratio}_{it-1}$		1.696	1.622		−0.081	−0.048
		(1.284)	(1.304)		(0.146)	(0.147)
$\text{Net Charge-Off Ratio}_{it-1}$		−1.323	−1.464		-0.341^{*}	−0.287
		(1.621)	(1.632)		(0.184)	(0.185)
$\text{Return on Assets}_{it-1}$		2.558	2.591		−0.068	−0.079
		(1.907)	(1.92)		(0.216)	(0.217)
$\text{Return on Equity}_{it-1}$		−0.158	−0.149		0.009	0.009
		(0.121)	(0.122)		(0.014)	(0.014)
$\text{Net Interest Margin}_{it-1}$		−0.711	−0.642		0.098	0.104^{*}
		(0.532)	(0.543)		(0.06)	(0.061)
$\text{Equity Ratio}_{it-1}$		−0.252	−0.279		−0.012	−0.01
		(0.268)	(0.268)		(0.03)	(0.03)
$\text{Resid. Mortg. Loans Ratio}_{it-1}$		−0.019	−0.016		0.002	0.003
		(0.027)	(0.027)		(0.003)	(0.003)
$\text{Corp \& Comm. Loans Ratio}_{it-1}$		0.005	0.002		-0.020^{***}	-0.020^{***}
		(0.022)	(0.023)		(0.003)	(0.003)
$\text{Cons. \& Retail Loans Ratio}_{it-1}$		-0.396^{***}	-0.392^{***}		0.009	0.008
		(0.053)	(0.056)		(0.006)	(0.006)
Loans HHI_{it-1}		-0.161^{***}	-0.162^{***}		0.001	0.001
		(0.02)	(0.02)		(0.002)	(0.002)
$\text{Int. \& Div. Income Ratio}_{it-1}$		−0.024	−0.031		0.005	0.005
		(0.045)	(0.045)		(0.005)	(0.005)
$\text{Non-Int Income Ratio}_{it-1}$		−0.003	−0.006		-0.006^{**}	-0.006^{**}
		(0.023)	(0.023)		(0.003)	(0.003)
Size_{it-1}		0.002	0.001		0.003^{***}	0.003^{***}
		(0.004)	(0.004)		(0.0004)	(0.0004)
$\text{Asset Growth}_{it-1}$		−0.016	−0.017		-0.043^{***}	-0.043^{***}
		(0.033)	(0.033)		(0.004)	(0.004)
Reputation_{it-1}		−0.02	−0.015		0.008^{**}	0.008^{**}
		(0.031)	(0.031)		(0.004)	(0.004)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	645	645	645	645	645	645
R^2	0.051	0.205	0.212	0.139	0.494	0.501
Adjusted R^2	0.039	0.176	0.176	0.128	0.475	0.479
Residual Std. Error	0.13	0.121	0.121	0.018	0.014	0.014
F Statistic	4.272^{***}	6.983^{***}	5.902^{***}	12.806^{***}	26.332^{***}	22.127^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.2: Average Treatment Effect Estimated through CBPS - Post Crisis Short Run

This table provides the results of the Average Treatment Effect estimated by Weighted Least Square (WLS) for the short run during the post-crisis period 2009-2014. Weights are the inverse of the Propensity Scores estimated by exactly identified CBPS over the full sample. Three models were estimated for two outcome variables, $\text{RWATA}_{it+1} - \text{RWATA}_{it-1}$ and $\text{LLPR}_{it+1} - \text{LLPR}_{it-1}$. The results in columns 1 and 4 include securitization and CB Issuance at time t only. Columns 2 and 5 control for bank specific pretreatment variables at $t-1$, and Columns 3 and 6 include the year effect. Country fixed effects are included in all columns.

	$\text{RWATA}_{it+1} - \text{RWATA}_{it-1}$			$\text{LLPR}_{it+1} - \text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.047^{**}	0.084	0.066	0.006^{***}	−0.004	−0.005
	(0.024)	(0.156)	(0.158)	(0.002)	(0.015)	(0.015)
$\text{Securitization}_{it}$	-0.112^{***}	-0.135^{***}	-0.134^{***}	−0.003	−0.001	−0.001
	(0.022)	(0.021)	(0.021)	(0.002)	(0.002)	(0.002)
CB Issuance_{it}	0.057^{***}	0.030	0.030^{*}	-0.003^{*}	−0.002	−0.002
	(0.02)	(0.018)	(0.018)	(0.002)	(0.002)	(0.002)
$\text{Loan Loss Provision Ratio}_{it-1}$		0.338	0.967		-0.834^{***}	-0.811^{***}
		(1.374)	(1.417)		(0.131)	(0.134)
$\text{Net Charge-Off Ratio}_{it-1}$		0.045	−1.212		−0.190	−0.158
		(1.832)	(1.865)		(0.174)	(0.177)
$\text{Return on Assets}_{it-1}$		-6.998^{***}	-5.726^{**}		−0.168	−0.056
		(2.215)	(2.235)		(0.211)	(0.212)
$\text{Return on Equity}_{it-1}$		0.093	0.086		−0.001	−0.003
		(0.057)	(0.057)		(0.005)	(0.005)
$\text{Net Interest Margin}_{it-1}$		2.452^{*}	2.196^{*}		0.091	0.130
		(1.268)	(1.328)		(0.121)	(0.126)
$\text{Equity Ratio}_{it-1}$		0.838^{**}	0.916^{**}		−0.042	−0.038
		(0.358)	(0.361)		(0.034)	(0.034)
$\text{Resid. Mortg. Loans Ratio}_{it-1}$		-0.070^{*}	-0.091^{**}		−0.002	−0.004
		(0.041)	(0.041)		(0.004)	(0.004)
$\text{Corp \& Comm. Loans Ratio}_{it-1}$		0.356^{***}	0.356^{***}		0.0003	0.001
		(0.031)	(0.031)		(0.003)	(0.003)
$\text{Cons. \& Retail Loans Ratio}_{it-1}$		−0.011	−0.005		−0.006	−0.006
		(0.072)	(0.072)		(0.007)	(0.007)
Loans HHI_{it-1}		−0.037	-0.052^{*}		−0.003	−0.003
		(0.027)	(0.027)		(0.003)	(0.003)
$\text{Int. \& Div. Income Ratio}_{it-1}$		0.061	0.083		0.004	0.004
		(0.095)	(0.095)		(0.009)	(0.009)
$\text{Non-Int Income Ratio}_{it-1}$		0.015	0.006		0.005	0.003
		(0.032)	(0.032)		(0.003)	(0.003)
Size_{it-1}		-0.012^{***}	-0.011^{**}		0.001	0.001^{*}
		(0.005)	(0.005)		(0.0004)	(0.0004)
$\text{Asset Growth}_{it-1}$		0.034	0.024		-0.014^{**}	-0.012^{**}
		(0.056)	(0.057)		(0.005)	(0.005)
Reputation_{it-1}		−0.063	−0.028		−0.005	−0.009
		(0.141)	(0.143)		(0.013)	(0.013)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	785	785	785	785	785	785
R^2	0.138	0.316	0.329	0.036	0.11	0.137
Adjusted R^2	0.129	0.296	0.305	0.026	0.083	0.106
Residual Std. Error	0.235	0.212	0.21	0.021	0.02	0.02
F Statistic	15.466^{***}	15.300^{***}	13.725^{***}	3.649^{***}	4.086^{***}	4.445^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.3: Average Treatment Effect Estimated through CBPS - Pre Crisis Long Run

This table provides the results of the Average Treatment Effect estimated by Weighted Least Square (WLS) for the long run during the pre-crisis period 2001-2004. Weights are the inverse of the Propensity Scores estimated by exactly identified CBPS over the full sample. Three models were estimated for two outcome variables, $\text{RWATA}_{it+3}-\text{RWATA}_{it-1}$ and $\text{LLPR}_{it+3}-\text{LLPR}_{it-1}$. The results in columns 1 and 4 include securitization and CB Issuance at time t only. Columns 2 and 5 control for bank specific pretreatment variables control at $t-1$, and Columns 3 and 6 include the year effect. Country fixed effects are included in all columns.

	$\text{RWATA}_{it+3}-\text{RWATA}_{it-1}$			$\text{LLPR}_{it+3}-\text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.020	−0.345	−0.433	-0.002^{**}	−0.001	0.0004
	(0.095)	(0.590)	(0.599)	(0.001)	(0.005)	(0.005)
$\text{Securitization}_{it}$	−0.009	−0.015	−0.012	0.001	0.0003	0.0003
	(0.062)	(0.066)	(0.066)	(0.001)	(0.001)	(0.001)
CB Issuance_{it}	−0.002	−0.008	−0.014	0.0004	−0.001	−0.001
	(0.086)	(0.097)	(0.097)	(0.001)	(0.001)	(0.001)
$\text{Loan Loss Provision Ratio}_{it-1}$		1.770	1.729		-0.767^{***}	-0.768^{***}
		(7.054)	(7.092)		(0.054)	(0.054)
$\text{Net Charge-Off Ratio}_{it-1}$		−9.284	−7.985		0.130^{**}	0.116^{*}
		(8.488)	(8.548)		(0.065)	(0.065)
$\text{Return on Assets}_{it-1}$		15.963	16.615		0.155	0.137
		(14.596)	(14.688)		(0.112)	(0.112)
$\text{Return on Equity}_{it-1}$		−0.360	−0.299		−0.001	−0.002
		(0.744)	(0.749)		(0.006)	(0.006)
$\text{Net Interest Margin}_{it-1}$		0.994	1.432		0.019	0.015
		(2.904)	(2.924)		(0.022)	(0.022)
$\text{Equity Ratio}_{it-1}$		−1.355	−1.483		−0.010	−0.008
		(1.378)	(1.381)		(0.011)	(0.011)
$\text{Resid. Mortg. Loans Ratio}_{it-1}$		0.199	0.233		0.0001	−0.0003
		(0.156)	(0.158)		(0.001)	(0.001)
$\text{Corp \& Comm. Loans Ratio}_{it-1}$		−0.132	−0.213		-0.006^{**}	-0.005^{**}
		(0.297)	(0.301)		(0.002)	(0.002)
Loans HHI_{it-1}		-0.301^{*}	-0.301^{*}		−0.002	−0.002
		(0.181)	(0.181)		(0.001)	(0.001)
$\text{Int. \& Div. Income Ratio}_{it-1}$		−0.120	−0.112		−0.002	−0.001
		(0.230)	(0.230)		(0.002)	(0.002)
$\text{Non-Int Income Ratio}_{it-1}$		0.083	0.069		−0.0002	−0.0001
		(0.154)	(0.156)		(0.001)	(0.001)
Size_{it-1}		0.030	0.030		0.0003^{**}	0.0003^{**}
		(0.020)	(0.020)		(0.0002)	(0.0002)
$\text{Asset Growth}_{it-1}$		0.003	−0.009		−0.001	−0.001
		(0.201)	(0.201)		(0.002)	(0.002)
Reputation_{it-1}		0.080	0.107		0.002^{*}	0.002
		(0.168)	(0.169)		(0.001)	(0.001)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	338	338	338	338	338	338
R^2	0.045	0.076	0.087	0.031	0.558	0.57
Adjusted R^2	0.021	0.012	0.014	0.007	0.527	0.536
Residual Std. Error	0.447	0.449	0.448	0.005	0.003	0.003
F Statistic	1.916^{*}	1.185	1.187	1.301	18.056^{***}	16.565^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.4: Average Treatment Effect Estimated through CBPS - Post Crisis Long Run

This table provides the results of the Average Treatment Effect estimated by Weighted Least Square (WLS) for the long run during the post-crisis period 2009-2014. Weights are the inverse of the Propensity Scores estimated by exactly identified CBPS over the full sample. Three models were estimated for two outcome variables, $\text{RWATA}_{it+3} - \text{RWATA}_{it-1}$ and $\text{LLPR}_{it+3} - \text{LLPR}_{it-1}$. The results in columns 1 and 4 include securitization and CB Issuance at time t only. Columns 2 and 5 control for bank specific pretreatment variables at $t-1$, and Columns 3 and 6 include the year effect. Country fixed effects are included in all columns.

	$\text{RWATA}_{it+3} - \text{RWATA}_{it-1}$			$\text{LLPR}_{it+3} - \text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.063^{***}	0.112	0.129	-0.004^{**}	-0.005	-0.006
	(0.018)	(0.138)	(0.138)	(0.002)	(0.012)	(0.012)
$\text{Securitization}_{it}$	-0.030^{*}	-0.013	-0.01	0.005^{***}	0.004^{***}	0.004^{***}
	(0.017)	(0.017)	(0.017)	(0.002)	(0.001)	(0.001)
CB Issuance_{it}	0.003	-0.015	-0.015	0.001	0.001	0.001
	(0.014)	(0.013)	(0.013)	(0.001)	(0.001)	(0.001)
Loan Loss Provision Ratio_{it-1}		1.855	1.304		-0.793^{***}	-0.823^{***}
		(1.31)	(1.351)		(0.111)	(0.114)
Net Charge-Off Ratio_{it-1}		-1.274	-0.609		0.031	0.001
		(1.641)	(1.672)		(0.139)	(0.142)
Return on Assets_{it-1}		-2.252	-2.82		0.227	0.218
		(2.319)	(2.326)		(0.196)	(0.197)
Return on Equity_{it-1}		0.102^{**}	0.098^{**}		-0.001	-0.001
		(0.043)	(0.043)		(0.004)	(0.004)
Net Interest Margin_{it-1}		-4.703^{***}	-3.953^{***}		-0.072	-0.067
		(0.93)	(0.989)		(0.079)	(0.084)
Equity Ratio_{it-1}		0.114	0.091		0.036	0.035
		(0.294)	(0.293)		(0.025)	(0.025)
Resid. Mortg. Loans Ratio_{it-1}		0.138^{***}	0.138^{***}		-0.009^{***}	-0.009^{***}
		(0.03)	(0.03)		(0.003)	(0.003)
Corp & Comm. Loans Ratio_{it-1}		-0.055^{**}	-0.046^{*}		-0.001	-0.001
		(0.027)	(0.027)		(0.002)	(0.002)
Cons. & Retail Loans Ratio_{it-1}		0.220^{***}	0.212^{***}		-0.005	-0.005
		(0.051)	(0.051)		(0.004)	(0.004)
Loans HHI_{it-1}		-0.093^{***}	-0.088^{***}		-0.005^{***}	-0.005^{***}
		(0.019)	(0.019)		(0.002)	(0.002)
Int. & Div. Income Ratio_{it-1}		-0.096	-0.103		0.011^{*}	0.011
		(0.077)	(0.077)		(0.007)	(0.007)
Non-Int Income Ratio_{it-1}		0.018	0.011		-0.002	-0.002
		(0.021)	(0.021)		(0.002)	(0.002)
Size_{it-1}		0.006	0.006		0.0002	0.0003
		(0.004)	(0.004)		(0.0003)	(0.0003)
Asset Growth_{it-1}		0.128^{**}	0.139^{***}		-0.005	-0.005
		(0.051)	(0.052)		(0.004)	(0.004)
Reputation_{it-1}		0.177^{*}	0.143		-0.01	-0.007
		(0.103)	(0.105)		(0.009)	(0.009)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	400	400	400	400	400	400
R^2	0.197	0.388	0.396	0.383	0.569	0.572
Adjusted R^2	0.181	0.351	0.356	0.37	0.542	0.543
Residual Std. Error	0.118	0.105	0.105	0.01	0.009	0.009
F Statistic	12.021^{***}	10.371^{***}	9.812^{***}	30.347^{***}	21.552^{***}	19.966^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.5: Overidentified GMM-CBPS estimates of the multinomial logit Propensity Score model

This table provides overidentified GMM-CBPS estimates of the multinomial logit Propensity Score model. Asymptotic standard errors in parenthesis. The model includes both year and country fixed effects.

	CB		SEC	
Intercept	-3.152	(9.725)	9.996	(6.853)
Loan Loss Provision Ratio$_{t-1}$	14.340^{***}	(0.537)	-11.607^{***}	(0.397)
Net Charge-Off Ratio$_{t-1}$	59.082^{***}	(0.418)	51.010^{***}	(0.441)
Return on Assets$_{t-1}$	-143484^{***}	(0.549)	-171997^{***}	(0.332)
Return on Equity$_{t-1}$	7.355^{***}	(1.626)	8.310^{***}	(1.239)
Net Interest Margin$_{t-1}$	75.357^{***}	(0.911)	63.400^{***}	(0.640)
Equity Ratio$_{t-1}$	14.360^{***}	(1.319)	17.131^{***}	(1.030)
Resid. Mortg. Loans Ratio$_{t-1}$	2.861^{***}	(0.663)	1.964^{***}	(0.473)
Corp & Comm. Loans Ratio$_{t-1}$	-0.358	(1.573)	-0.188	(1.266)
Cons. & Retail Loans Ratio$_{t-1}$	-1.016	(2.262)	-1.688	(1.845)
Loans HHI$_{t-1}$	-1.476	(1.329)	-1.574^{*}	(0.845)
Int. & Div. Income Ratio$_{t-1}$	-1.482	(1.309)	-0.216	(0.952)
Non-Int Income Ratio$_{t-1}$	0.480	(0.855)	-0.290	(0.636)
Size$_{t-1}$	0.109	(0.365)	-0.245	(0.242)
Asset Growth$_{t-1}$	-0.545^{*}	(0.321)	-1.109^{***}	(0.187)
Reputation$_{t-1}$	-0.018	(0.677)	-3.178^{***}	(0.564)
FC$_t$ × Loan Loss Provision Ratio$_{t-1}$	21.198^{***}	(0.148)	17.094^{***}	(0.107)
FC$_t$ × Net Charge-Off Ratio$_{t-1}$	-47.360^{***}	(0.315)	-54.391^{***}	(0.330)
FC$_t$ × Return on Assets$_{t-1}$	157.262^{***}	(0.233)	177.565^{***}	(0.119)
FC$_t$ × Return on Equity$_{t-1}$	-6.591^{***}	(1.629)	-7.679^{***}	(1.335)
FC$_t$ × Net Interest Margin$_{t-1}$	-29.446^{***}	(1.376)	-3.523^{***}	(1.082)
FC$_t$ × Equity Ratio$_{t-1}$	-19.337^{***}	(1.655)	-26.388^{***}	(1.335)
FC$_t$ × Resid. Mortg. Loans Ratio$_{t-1}$	-2.398^{***}	(0.639)	-2.734^{***}	(0.510)
FC$_t$ × Corp & Comm. Loans Ratio$_{t-1}$	1.004	(1.321)	0.466	(1.033)
FC$_t$ × Cons. & Retail Loans Ratio$_{t-1}$	0.516	(2.617)	1.114	(2.045)
FC$_t$ × Loans HHI$_{t-1}$	1.474	(1.473)	1.286	(1.230)
FC$_t$ × Int. & Div. Income Ratio$_{t-1}$	7.618^{***}	(0.779)	3.399^{***}	(0.559)
FC$_t$ × Non-Int Income Ratio$_{t-1}$	-1.259	(1.501)	-0.002	(1.264)
FC$_t$ × Size$_{t-1}$	-0.413	(2.305)	-0.297	(1.720)
FC$_t$ × Asset Growth$_{t-1}$	1.610^{***}	(0.549)	1.073^{***}	(0.380)
FC$_t$ × Reputation$_{t-1}$	2.445^{***}	(0.420)	2.394^{***}	(0.226)
Observations	1700			
Log-Likelihood	-1179.228			

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B.6: t-test for equality of means of pretreatment covariates before and after weighting using the inverse of PS estimated with overidentified GMM-CBPS

This table compares the means of the pretreatment covariates of banks belonging to different treatment groups using a *paired-sample t-test*. The Null hypothesis is: *Means are equal across various categories of banks.* Columns (1)-(3) contain differences in unweighted sample averages; columns (4)-(6) contain differences in sample averages weighted by the inverse of the multinomial logit propensity scores estimated by overidentified GMM-CBPS. Loan Hirschman-Herfindahl Index (Loan HHI) is computed using five loans shares (real estate, commercial and industrial, agricultural, consumer, and other loans) and measures the concentration of the loan portfolio of a bank. Interest and dividend income ratio is the ratio of interest and dividend income from securities to total interest income. It measures the return from investments different from the traditional income sources of a bank (loans). The non-interest income ratio is measured as non-interest income divided by net operating revenue. It gauges the overall diversification status of a bank. A low ratio indicates that a bank is still focused on the traditional source of income (i.e., interest income). Size is measured as the natural log of total assets. Reputation is measured as a ratio of the letter of guarantee to total assets.

	Original sample			Weighted sample		
	(1) SEC-None	(2) CB-None	(3) SEC-CB	(4) SEC-None	(5) CB-None	(6) SEC-CB
Loan Loss Provision Ratio	0.000	0.001	0.000	0.000	0.000	0.000
Net Charge-Off Ratio	0.001**	0.001***	0.000	0.000	0.000	0.000
Return on Assets	0.003***	−0.002***	0.005***	0.001	−0.001***	0.003***
Return on Equity	0.035***	−0.048***	0.083***	0.004	−0.023**	0.028
Net Interest Margin	0.003**	−0.006***	0.009***	0.002**	−0.003***	0.006***
Equity Ratio	0.004	−0.013***	0.018***	0.007*	−0.011***	0.019***
Resid. Mortg. Loans Ratio	0.046**	0.000	0.046*	−0.020	0.027	−0.048
Corp & Comm. Loans Ratio	0.015	−0.016	0.031	−0.001	−0.012	0.010
Cons. & Retail Loans Ratio	0.006	0.014*	−0.008	0.003	0.001	0.002
Loan HHI	0.056**	0.021	0.035	0.033	−0.016	0.048
Int. & Div. Income Ratio	−0.018	−0.036***	0.018	0.004	−0.008	0.011
Non-Int Income Ratio	0.109***	−0.118***	0.227***	0.060**	−0.054*	0.115***
Size	0.521***	1.419***	−0.898***	−0.135	0.518***	−0.653**
Asset Growth	0.043***	−0.038***	0.080***	0.031*	−0.020*	0.051***
Reputation	0.043***	0.010	0.033**	0.015*	0.004	0.011

*p<0.1; **p<0.05; ***p<0.01

Table B.7: Average Short Run Treatment Effect Estimated with Overidentified CBPS

This table provides the results of the Short Run Average Treatment Effect estimated by Weighted Least Square (WLS) over the full sample period. Weights are the inverse of the Propensity Scores estimated by overidentified CBPS. Estimations include the treatment variable, the financial crisis dummy and bank-specific covariates in three models, respectively. The outcome variable are $\text{RWATA}_{it+1}-\text{RWATA}_{it-1}$ and $\text{LLPR}_{it+1}-\text{LLPR}_{it-1}$. The results in columns 1 and 4 include securitization and CB Issuance at time t, the financial crisis dummy and the interaction terms of securitization and CB Issuance with the financial crisis dummy. Columns 2 and 5 include bank specific variables control at $t-1$ and Columns 3 and 6 include the year effect. Country fixed effects are included in all columns.

	$\text{RWATA}_{it+1}-\text{RWATA}_{it-1}$			$\text{LLPR}_{it+1}-\text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.013	-0.247^{**}	-0.179	0.001	-0.027^{***}	-0.021^{**}
	(0.024)	(0.112)	(0.114)	(0.002)	(0.008)	(0.008)
$\text{Securitization}_{it}$	-0.004	0.003	0.003	0.001	0.001	0.001
	(0.021)	(0.021)	(0.021)	(0.002)	(0.001)	(0.001)
CB Issuance_{it}	-0.025	-0.015	-0.016	-0.002	-0.004^{**}	-0.004^{**}
	(0.027)	(0.027)	(0.028)	(0.002)	(0.002)	(0.002)
Financial Crisis	0.01	0.009		0.004^{**}	0.003^{**}	
	(0.02)	(0.02)		(0.001)	(0.001)	
$\text{FC} \times \text{Securitization}_{it}$	-0.116^{***}	-0.116^{***}	-0.118^{***}	-0.002	-0.002	-0.001
	(0.03)	(0.029)	(0.029)	(0.002)	(0.002)	(0.002)
$\text{FC} \times \text{CB Issuance}_{it}$	0.002	-0.029	-0.026	-0.001	0.002	0.001
	(0.033)	(0.033)	(0.033)	(0.002)	(0.002)	(0.002)
$\text{Loan Loss Provision Ratio}_{it-1}$		4.624^{***}	4.343^{***}		-0.582^{***}	-0.542^{***}
		(1.212)	(1.238)		(0.087)	(0.089)
$\text{Net Charge-Off Ratio}_{it-1}$		-0.709	-1.434		-0.355^{***}	-0.309^{***}
		(1.541)	(1.572)		(0.111)	(0.113)
$\text{Return on Assets}_{it-1}$		-2.926^{*}	-2.468		0.024	0.023
		(1.577)	(1.605)		(0.114)	(0.115)
$\text{Return on Equity}_{it-1}$		0.115^{**}	0.115^{**}		0.004	0.003
		(0.058)	(0.058)		(0.004)	(0.004)
$\text{Net Interest Margin}_{it-1}$		-0.95	-1.064		0.014	0.023
		(0.752)	(0.772)		(0.054)	(0.055)
$\text{Equity Ratio}_{it-1}$		0.843^{***}	0.806^{***}		-0.013	-0.012
		(0.256)	(0.258)		(0.018)	(0.019)
$\text{Resid. Mortg. Loans Ratio}_{it-1}$		0.045^{*}	0.046^{*}		-0.001	-0.001
		(0.027)	(0.027)		(0.002)	(0.002)
$\text{Corp \& Comm. Loans Ratio}_{it-1}$		0.069^{***}	0.072^{***}		-0.003	-0.002
		(0.023)	(0.023)		(0.002)	(0.002)
$\text{Cons. \& Retail Loans Ratio}_{it-1}$		-0.153^{***}	-0.147^{***}		-0.00003	-0.002
		(0.052)	(0.053)		(0.004)	(0.004)
Loans HHI_{it-1}		-0.132^{***}	-0.133^{***}		0.001	0.001
		(0.016)	(0.016)		(0.001)	(0.001)
$\text{Int. \& Div. Income Ratio}_{it-1}$		0.012	0.013		0.0004	0.002
		(0.057)	(0.057)		(0.004)	(0.004)
$\text{Non-Int Income Ratio}_{it-1}$		0.059^{**}	0.057^{**}		-0.003^{*}	-0.003^{*}
		(0.025)	(0.025)		(0.002)	(0.002)
Size_{it-1}		0.011^{***}	0.011^{***}		0.001^{***}	0.001^{***}
		(0.004)	(0.004)		(0.0003)	(0.0003)
$\text{Asset Growth}_{it-1}$		0.038	0.051		-0.006^{**}	-0.006^{**}
		(0.039)	(0.04)		(0.003)	(0.003)
Reputation_{it-1}		0.009	-0.002		0.004	0.004
		(0.044)	(0.045)		(0.003)	(0.003)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1700	1700	1700	1700	1700	1700
R^2	0.04	0.101	0.119	0.015	0.089	0.113
Adjusted R^2	0.034	0.087	0.099	0.008	0.075	0.093
Residual Std. Error	0.18	0.175	0.174	0.013	0.013	0.013
F Statistic	6.399^{***}	7.222^{***}	6.069^{***}	2.315^{***}	6.293^{***}	5.710^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.8: Average Long Run Treatment Effect Estimated with Overidentified CBPS

This table provides the results of the Long Run Average Treatment Effect estimated by Weighted Least Square (WLS) over the full sample period. Weights are the inverse of the Propensity Scores estimated by overidentified CBPS. Estimations include the treatment variable, the financial crisis dummy and bank-specific covariates in three models, respectively. The outcome variable are $\text{RWATA}_{it+3} - \text{RWATA}_{it-1}$ and $\text{LLPR}_{it+3} - \text{LLPR}_{it-1}$. The results in columns 1 and 4 include securitization and CB Issuance at time t, the financial crisis dummy and the interaction terms of securitization and CB Issuance with the financial crisis dummy. Columns 2 and 5 include bank specific variables control at $t-1$ and Columns 3 and 6 include the year effect. Country fixed effects are included in all columns.

	$\text{RWATA}_{it+3} - \text{RWATA}_{it-1}$			$\text{LLPR}_{it+3} - \text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.072***	0.168**	0.117	0.010	0.034	0.034
	(0.019)	(0.085)	(0.088)	(0.010)	(0.050)	(0.052)
$\text{Securitization}_{it}$	−0.025	−0.012	−0.010	−0.010	−0.010	−0.010
	(0.015)	(0.014)	(0.014)	(0.008)	(0.008)	(0.008)
CB Issuance_{it}	−0.029	−0.035*	−0.021	−0.010	−0.008	−0.011
	(0.020)	(0.019)	(0.019)	(0.011)	(0.011)	(0.011)
Financial Crisis	−0.067***	−0.067***		−0.010	−0.008	
	(0.017)	(0.016)		(0.009)	(0.009)	
FC × $\text{Securitization}_{it}$	−0.008	−0.015	−0.015	0.011	0.010	0.010
	(0.024)	(0.023)	(0.023)	(0.013)	(0.013)	(0.014)
FC × CB Issuance_{it}	0.058**	0.040	0.028	0.010	0.007	0.010
	(0.027)	(0.025)	(0.025)	(0.014)	(0.015)	(0.015)
$\text{Loan Loss Provision Ratio}_{it-1}$		1.811*	1.399		−1.483**	−1.480**
		(1.082)	(1.094)		(0.638)	(0.647)
$\text{Net Charge-Off Ratio}_{it-1}$		−2.554*	−2.403*		−0.089	−0.210
		(1.359)	(1.385)		(0.801)	(0.819)
$\text{Return on Assets}_{it-1}$		−1.055	−1.318		−0.019	−0.139
		(1.304)	(1.339)		(0.769)	(0.792)
$\text{Return on Equity}_{it-1}$		0.002	−0.007		−0.013	−0.004
		(0.046)	(0.047)		(0.027)	(0.028)
$\text{Net Interest Margin}_{it-1}$		0.443	0.413		−0.103	−0.048
		(0.550)	(0.565)		(0.324)	(0.334)
$\text{Equity Ratio}_{it-1}$		0.235	0.282		0.027	−0.007
		(0.200)	(0.204)		(0.118)	(0.121)
$\text{Resid. Mortg. Loans Ratio}_{it-1}$		0.086***	0.080***		−0.004	−0.006
		(0.021)	(0.021)		(0.012)	(0.012)
$\text{Corp \& Comm. Loans Ratio}_{it-1}$		−0.029	−0.027		0.020*	0.020*
		(0.018)	(0.018)		(0.010)	(0.011)
$\text{Cons. \& Retail Loans Ratio}_{it-1}$		−0.221***	−0.202***		0.006	0.003
		(0.040)	(0.041)		(0.023)	(0.024)
Loans HHI_{it-1}		−0.154***	−0.156***		0.0003	0.001
		(0.012)	(0.012)		(0.007)	(0.007)
$\text{Int. \& Div. Income Ratio}_{it-1}$		−0.002	0.004		0.001	−0.001
		(0.042)	(0.042)		(0.025)	(0.025)
$\text{Non-Int Income Ratio}_{it-1}$		−0.012	−0.014		0.004	0.002
		(0.019)	(0.019)		(0.011)	(0.011)
Size_{it-1}		0.002	0.002		−0.001	−0.001
		(0.003)	(0.003)		(0.002)	(0.002)
$\text{Asset Growth}_{it-1}$		0.089***	0.101***		−0.024	−0.017
		(0.030)	(0.031)		(0.018)	(0.018)
Reputation_{it-1}		0.046	0.034		−0.013	−0.011
		(0.030)	(0.030)		(0.018)	(0.018)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1250	1250	1250	1250	1250	1250
R^2	0.128	0.291	0.303	0.007	0.019	0.029
Adjusted R^2	0.12	0.276	0.283	−0.001	−0.002	0.001
Residual Std. Error	0.129	0.117	0.116	0.069	0.069	0.069
F Statistic	16.537***	19.283***	15.058***	0.839	0.887	1.049

*$p<0.1$; **$p<0.05$; ***$p<0.01$

Table B.9: t-test for equality of means of pretreatment covariates before and after weighting using the inverse of PS estimated with GBM

This table compares the means of the pretreatment covariates of banks belonging to different treatment groups using *paired-sample t-test*. The Null hypothesis is: *Means are equal across various categories of banks.* Columns (1)-(3) contain differences in unweighted sample averages; columns (4)-(6) contain differences in sample averages weighted by the inverse of the propensity scores estimated using the GBM method. Loan Hirschman-Herfindahl Index (Loan HHI) is computed using five loans shares (real estate, commercial and industrial, agricultural, consumer, and other loans) and measures the concentration of the loan portfolio of a bank. Interest and dividend income ratio is the ratio of interest and dividend income from securities to total interest income. It measures the return from investments different from the traditional income sources of a bank (loans). The non-interest income ratio is measured as non-interest income divided by net operating revenue. It gauges the overall diversification status of a bank. A low ratio indicates that a bank is still focused on the traditional source of income (i.e., interest income). Size is measured as the natural log of total assets. Reputation is measured as a ratio of the letter of guarantee to total assets.

	Original sample			Weighted sample		
	(1) SEC-None	(2) CB-None	(3) SEC-CB	(4) SEC-None	(5) CB-None	(6) SEC-CB
Loan Loss Provision Ratio	0.000	0.001	0.000	0.001	0.000	0.000
Net Charge-Off Ratio	0.001**	0.001***	0.000	0.000	0.000*	0.000
Return on Assets	0.003***	−0.002***	0.005***	0.000	−0.001***	0.002**
Return on Equity	0.035***	−0.048***	0.083***	−0.004	−0.023**	0.019
Net Interest Margin	0.003**	−0.006***	0.009***	0.002**	−0.003***	0.005***
Equity Ratio	0.004	−0.013***	0.018***	0.004	−0.008***	0.012***
Resid. Mortg. Loans Ratio	0.046**	0.000	0.046*	0.007	−0.020	0.027
Corp & Comm. Loans Ratio	0.015	−0.016	0.031	0.011	0.010	0.001
Cons. & Retail Loans Ratio	0.006	0.014*	−0.008	0.012	0.000	0.012
Loan HHI	0.056**	0.021	0.035	0.044	0.038*	0.006
Int. & Div. Income Ratio	−0.018	−0.036***	0.018	−0.009	−0.021***	0.012
Non-Int Income Ratio	0.109***	−0.118***	0.227***	0.024	−0.031	0.055
Size	0.521***	1.419***	−0.898***	0.109	0.605***	−0.496**
Asset Growth	0.043***	−0.038***	0.080***	0.022	−0.025**	0.047***
Reputation	0.043***	0.010	0.033**	0.019**	0.008	0.011

*$p<0.1$; **$p<0.05$; ***$p<0.01$

Table B.10: Average Short Run Treatment Effect Estimated with GBM

This table provides the results of the Short Run Average Treatment Effect estimated by Weighted Least Square (WLS) over the full sample period. Weights are the inverse of the Propensity Scores estimated by GBM. Estimations include the treatment variable, the financial crisis dummy and bank-specific covariates in three models, respectively. The outcome variable are $\text{RWATA}_{it+1} - \text{RWATA}_{it-1}$ and $\text{LLPR}_{it+1} - \text{LLPR}_{it-1}$. The results in columns 1 and 4 include securitization and CB Issuance at time t, the financial crisis dummy and the interaction terms of securitization and CB Issuance with the financial crisis dummy. Columns 2 and 5 include bank specific variables control at $t-1$ and Columns 3 and 6 include the year effect. Country fixed effects are included in all columns.

	$\text{RWATA}_{it+1} - \text{RWATA}_{it-1}$			$\text{LLPR}_{it+1} - \text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.024	0.066	0.042	0.001	-0.017^{**}	-0.012
	(0.015)	(0.125)	(0.111)	(0.003)	(0.007)	(0.008)
$\text{Securitization}_{it}$	-0.005	-0.006	-0.007	0.0004	0.0003	0.0005
	(0.014)	(0.015)	(0.015)	(0.001)	(0.001)	(0.001)
CB Issuance_{it}	-0.019	-0.005	-0.003	-0.001	-0.003^{*}	-0.003^{*}
	(0.015)	(0.017)	(0.018)	(0.002)	(0.002)	(0.002)
Financial Crisis	-0.024^{*}	-0.029^{**}		0.003^{***}	0.003^{***}	
	(0.014)	(0.014)		(0.001)	(0.001)	
FC × $\text{Securitization}_{it}$	-0.079^{**}	-0.061^{*}	-0.061^{**}	0.001	0.002	0.002
	(0.033)	(0.031)	(0.029)	(0.002)	(0.002)	(0.002)
FC × CB Issuance_{it}	0.02	0.004	0.001	-0.0002	0.001	0.001
	(0.021)	(0.022)	(0.023)	(0.002)	(0.002)	(0.002)
Loan Loss Provision Ratio_{it-1}		0.563	0.888		-0.592^{***}	-0.533^{***}
		(1.245)	(1.228)		(0.1)	(0.099)
Net Charge-Off Ratio_{it-1}		-0.001	-0.449		-0.162	-0.133
		(0.892)	(0.886)		(0.173)	(0.174)
Return on Assets_{it-1}		-0.855	-0.662		-0.013	-0.027
		(1.233)	(1.201)		(0.172)	(0.184)
Return on Equity_{it-1}		-0.003	0.004		-0.001	-0.0001
		(0.043)	(0.046)		(0.004)	(0.004)
Net Interest Margin_{it-1}		0.289	0.16		-0.022	-0.018
		(0.863)	(0.866)		(0.043)	(0.046)
Equity Ratio_{it-1}		0.251	0.259		-0.001	0.001
		(0.264)	(0.265)		(0.015)	(0.015)
Resid. Mortg. Loans Ratio_{it-1}		0.034	0.037		-0.003^{***}	-0.003^{***}
		(0.024)	(0.024)		(0.001)	(0.001)
Corp & Comm. Loans Ratio_{it-1}		-0.008	-0.005		-0.0005	-0.0002
		(0.03)	(0.031)		(0.002)	(0.002)
Cons. & Retail Loans Ratio_{it-1}		-0.118^{**}	-0.121^{**}		-0.002	-0.003
		(0.06)	(0.059)		(0.002)	(0.002)
Loans HHI_{it-1}		-0.121^{***}	-0.126^{***}		0.001	0.001
		(0.019)	(0.02)		(0.001)	(0.001)
Int. & Div. Income Ratio_{it-1}		-0.009	-0.005		0.001	0.002
		(0.048)	(0.048)		(0.001)	(0.001)
Non-Int Income Ratio_{it-1}		0.022	0.018		-0.001	-0.001
		(0.015)	(0.016)		(0.001)	(0.001)
Size_{it-1}		0.003	0.003		0.001^{***}	0.001^{***}
		(0.005)	(0.005)		(0.0003)	(0.0002)
Asset Growth_{it-1}		0.008	0.007		-0.003	-0.004
		(0.025)	(0.026)		(0.003)	(0.003)
Reputation_{it-1}		0.018	0.015		0.005^{*}	0.005^{**}
		(0.038)	(0.036)		(0.003)	(0.002)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1700	1700	1700	1700	1700	1700
Log Likelihood	295.467	345.498	354.568	4493.57	4554.331	4581.183
Akaike Inf. Crit.	-566.934	-636.996	-633.136	-8963.14	-9054.661	-9086.366

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.11: Average Long Run Treatment Effect Estimated with GBM

This table provides the results of the Long Run Average Treatment Effect estimated by Weighted Least Square (WLS) over the full sample period. Weights are the inverse of the Propensity Scores estimated by GBM. Estimations include the treatment variable, the financial crisis dummy and bank-specific covariates in three models, respectively. The outcome variable are $\text{RWATA}_{it+3}-\text{RWATA}_{it-1}$ and $\text{LLPR}_{it+3}-\text{LLPR}_{it-1}$. The results in columns 1 and 4 include securitization and CB Issuance at time t, the financial crisis dummy and the interaction terms of securitization and CB Issuance with the financial crisis dummy. Columns 2 and 5 include bank specific variables control at $t-1$ and Columns 3 and 6 include the year effect. Country fixed effects are included in all columns.

	$\text{RWATA}_{it+3}-\text{RWATA}_{it-1}$			$\text{LLPR}_{it+3}-\text{LLPR}_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.064^{***}	0.007	−0.065	0.004	0.027	0.026
	(0.024)	(0.252)	(0.253)	(0.005)	(0.041)	(0.035)
$\text{Securitization}_{it}$	0.009	0.001	−0.001	−0.005	−0.004	−0.004
	(0.048)	(0.045)	(0.043)	(0.006)	(0.005)	(0.005)
CB Issuance_{it}	−0.036	−0.026	−0.001	−0.003	−0.004	−0.006
	(0.027)	(0.029)	(0.034)	(0.005)	(0.005)	(0.005)
Financial Crisis	-0.067^{***}	-0.072^{***}		−0.005	−0.003	
	(0.022)	(0.021)		(0.007)	(0.006)	
FC × $\text{Securitization}_{it}$	−0.073	−0.019	−0.018	0.008	0.007	0.008
	(0.061)	(0.055)	(0.052)	(0.007)	(0.007)	(0.006)
FC × CB Issuance_{it}	0.052^{*}	0.027	0.003	0.004	0.006	0.007
	(0.031)	(0.034)	(0.039)	(0.006)	(0.006)	(0.006)
Loan Loss Provision Ratio_{it-1}		1.278	0.624		-1.190^{***}	-1.206^{***}
		(1.486)	(1.523)		(0.313)	(0.334)
Net Charge-Off Ratio_{it-1}		−1.787	−1.607		−0.027	−0.046
		(1.594)	(1.541)		(0.122)	(0.093)
Return on Assets_{it-1}		1.128	2.314		0.13	0.111
		(1.571)	(1.982)		(0.172)	(0.128)
Return on Equity_{it-1}		−0.022	−0.038		−0.008	−0.004
		(0.042)	(0.045)		(0.012)	(0.009)
Net Interest Margin_{it-1}		1.493	1.417		−0.138	−0.11
		(1.063)	(1.041)		(0.124)	(0.117)
Equity Ratio_{it-1}		−0.366	−0.48		−0.005	−0.017
		(0.434)	(0.506)		(0.029)	(0.031)
Resid. Mortg. Loans Ratio_{it-1}		0.137^{**}	0.134^{**}		-0.006^{***}	-0.007^{**}
		(0.054)	(0.053)		(0.002)	(0.004)
Corp & Comm. Loans Ratio_{it-1}		-0.060^{**}	-0.059^{**}		0.011	0.012
		(0.025)	(0.025)		(0.011)	(0.011)
Cons. & Retail Loans Ratio_{it-1}		-0.258^{***}	-0.220^{***}		0.003	0.0004
		(0.074)	(0.073)		(0.004)	(0.004)
Loans HHI_{it-1}		-0.208^{***}	-0.201^{***}		0	0.001
		(0.031)	(0.03)		(0.002)	(0.001)
Int. & Div. Income Ratio_{it-1}		−0.051	−0.046		0.002	0.003
		(0.059)	(0.059)		(0.003)	(0.003)
Non-Int Income Ratio_{it-1}		0.024	0.023		0.002	0.002
		(0.016)	(0.016)		(0.002)	(0.002)
Size_{it-1}		0.013	0.012		−0.001	−0.001
		(0.009)	(0.009)		(0.001)	(0.002)
Asset Growth_{it-1}		0.003	0.003		−0.012	−0.008
		(0.037)	(0.043)		(0.011)	(0.008)
Reputation_{it-1}		0.114^{**}	0.123^{**}		−0.013	−0.013
		(0.053)	(0.057)		(0.014)	(0.014)
Year Effect	No	No	Yes	No	No	Yes
Country Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1250	1250	1250	1250	1250	1250
Log Likelihood	−714.231	−679.589	−669.801	1334.596	1341.525	1345.055
Akaike Inf. Crit.	1452.461	1413.179	1411.601	−2645.192	−2629.051	−2618.109

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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