Working Paper Series

No 22 / September 2016

Arbitraging the Basel securitization framework: Evidence from German ABS investment

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Abstract

This paper provides evidence for regulatory arbitrage within the class of asset-backed securities (ABS) based on individual asset holding data of German banks. I find that banks operating with tight regulatory constraints exploit the low risk-sensitivity of rating-contingent capital requirements for ABS. Unlike unconstrained banks they systematically pick the securities with the highest yield and the lowest collateral performance among ABS with the same regulatory risk weight. This reaching for yield allows constrained banks to increase the return on the capital required for an ABS investment by a factor of four.

Keywords: Regulatory arbitrage, asset-backed securities, reaching for yield, credit ratings

JEL classification: G01, G21, G24, G28.

Risk-sensitive capital requirements are the first pillar of bank regulation under the Basel II and the Basel III framework. External and internal credit ratings are used to determine the level of risk in each bank asset and to set the appropriate risk weight and maximum leverage allowed. Yet, this rating-contingent regulation can have unintended consequences if credit ratings do not discriminate between systematic and idiosyncratic risks. Banks might "herd into the most systematically risky investments, making simultaneous bank failures particularly sensitive to economic downturns (Iannotta and Pennacchi, 2012, p. 2)."[1]

The calibration of Basel risk weights to credit ratings is more critical in asset classes that exhibit high levels of systematic risk. A prominent example is the securitization market for asset-backed securities (ABS) whose losses tend to be highly correlated and occur mainly during economic downturns (Coval, Jurek, and Stafford, 2009; Wojtowicz, 2014).[2] The high systematic risk of ABS is not fully captured by credit ratings which are primarily designed to reflect physical but not risk-neutral expected default losses. As a result, thousands of ABS tranches had to be downgraded to junk in 2008 and 2009. This "credit rating crisis" (Benmelech and Dlugosz, 2009b) attracted the attention of bank regulators who were concerned that rating-based capital requirements were undercharging banks for exposures to high systematic risk.[3] The Basel Committee on Banking Supervision (2014) named the "mechanic reliance on external ratings" and "insufficient risk sensitivity" as two major weaknesses of its regulatory framework for securitization exposures.

The literature documents little evidence that banks exploit these regulatory weaknesses and arbitrage rating-contingent ABS risk weights. The main reason for this gap in the literature is the lack of micro data on ABS investments of banks. Erel, Nadauld, and Stulz (2014) do study bank investments into ABS but they analyze aggregate holdings and not individual asset choices. Merrill, Nadauld, and Strahan (2014), Chernenko, Hanson, and Sunderam (2015), and Ellul, Jotikasthira, Lundblad, and Wang (2015) exploit security-level data on ABS investments but they focus on insurance companies and funds which are arguably better capitalized and less prone to illiquidity risk and creditor runs than banks.

[1] See also Kupiec (2004) and Pennacchi (2006).

[2] I use the term asset-backed securities for all different types of structured debt securities, including residential and commercial mortgage-backed securities, collateralized debt and loan obligations, and other securities that use a variety of different loan types as collateral (student loans, car loans, etc.).

[3] "[...] many models (of credit rating agencies) severely underestimated the concentration of systemic risk through securitization and resecuritization (Basel Committee on Banking Supervision, 2012, p.4)."

Thus far *bank demand* for ABS has essentially remained a black box.

This paper explores a unique data set that records the quarterly ABS holdings of German banks between 2007 and 2012 on a security-by-security basis.[4] The high level of resolution allows me to show that regulatory arbitrage incentives do indeed influence the individual asset choices of banks in the ABS market. Banks systematically buy the ABS that promise the highest yields and have the highest systematic risk within each risk weight category—they "reach for yield" (Becker and Ivashina, 2015).[5] An increase of the yield spread by one percentage point increases the probability that the bank buys an ABS in a given risk weight category by 34% relative to the sample average. This risk weight arbitrage is most pronounced for banks with tight regulatory constraints. Banks with capital adequacy ratios (CARs) close to 8% (= the minimum allowed by the Basel regulator) reach for yield most aggressively.[6] Conditional on the risk weight of ABS, an increase of the yield spread by one percentage point almost doubles the probability that a constrained bank invests into the security and increases the portfolio share of the ABS by 1.5%. For higher CARs (laxer regulatory constraints) the effect decreases rapidly. Banks with CARs above 17% do not reach for yield at all.

To quantify the possible extent of this risk weight arbitrage, I compare the ABS investments of constrained banks, which reach for yield, to the ABS bought by banks that are not constrained by regulation and do not arbitrage risk weights. I find a striking mismatch between the average risk (as proxied by the yield spread) and the average capital requirement of these ABS. Constrained banks buy *riskier* ABS with *lower* capital requirements than unconstrained banks. This finding suggests that rating-based regulation does indeed undercharge constrained banks for risk taking. Banks with low CARs (tight constraints) buy ABS with, on average, 25bps *higher* yield spreads than unconstrained banks. Yet, the capital requirement per Euro invested in the ABS is, on average, 4.8 Cent *lower*. This regulatory arbitrage appears to be highly profitable for constrained banks that need to economize on regulatory capital. A simple back-of-the-envelope estimation suggests that the ABS invest-

[4]The data set is maintained by the Deutsche Bundesbank (German Central Bank) and covers only banks residing in Germany and the period 2007–2012.

[5]Collin-Dufresne, Goldstein, and Yang (2012) show that ABS yield spreads are a good proxy for systematic risk.

[6]The CAR is defined as eligible bank equity over total risk-weighted assets and has to be at least 8% under Basel II. I use the three-months lag to ensure that ABS purchases do not tighten the regulatory constraint mechanically.

ments of constrained banks promise a return on required equity approximately four times higher than the ABS bought by unconstrained banks. The four times higher return on equity is likely to reflect a significant increase in bank risk. It seems problematic that especially constrained banks, which the regulator considers worst capitalized and most fragile, can arbitrage ABS risk weights to such a large extent.

While I argue that the strong correlation between tight regulatory constraints and aggressive reaching for yield is relevant from a financial stability perspective in and of itself, I concede that it does not prove a causal relation. There could be alternative explanations besides regulatory arbitrage why only constrained banks reach for yield. I try to address this concern in three different ways. First, I control for bank size because larger banks tend to operate with less equity and are also different in terms of transaction costs, too-big-to-fail subsidies, and sophistication.[7] Second and more importantly, I estimate all regressions with and without bank fixed effects. If anything, the results become stronger when bank fixed effects absorb time-invariant variation in bank characteristics like different business models, bank culture, or governance quality. Finally, I check whether agency problems and risk shifting incentives alone can explain reaching for yield behavior. To test this idea, I replace the regulatory CAR (defined as equity over *risk-weighted* assets) by the leverage ratio (defined as equity over *unweighted* assets) assuming that agency problems are larger in highly leveraged banks (e.g. Jensen and Meckling, 1979; Admati, DeMarzo, Hellwig, and Pfleiderer, 2011). The correlation between the weighted and the unweighted leverage ratio is only 0.16 in my sample. But if agency problems and not regulatory arbitrage incentives explain reaching for yield, then the unweighted leverage ratio should have at least as much predictive power as banks' CARs. Yet, this is not the case. Only banks that are highly leveraged in the *regulatory* sense (low CARs) arbitrage ABS risk weights.

High systematic risk is not the only reason for the large regulatory arbitrage opportunities in the securitization market. Regulators are also concerned about "rating agency errors flowing through to regulatory capital requirements (Basel Committee on Banking Supervision, 2012, p. 4)." Existing empirical evidence suggests that rating standards for ABS are indeed low (Benmelech and Dlugosz, 2009a; Ashcraft, Goldsmith-Pinkham, and Vickery, 2010; Griffin and Tang, 2012). ABS ratings are often biased or "inflated" due to

[7] In untabulated regressions I also control for banks' total ABS holdings, the amount of collateral that banks securitize themselves, and the amount of derivatives trading to proxy for sophistication and expertise.

ratings shopping and agency problems on the side of the credit rating agencies (He, Qian, and Strahan, 2012; Cornaggia and Cornaggia, 2013; Efing and Hau, 2015).[8] This rating bias allows high-yield ABS to move to regulatory buckets with lower risk weights, thereby relaxing regulatory constraints of banks buying these ABS. To test this hypothesis, I identify ABS that have received a rating that is too good compared to the ratings of other securities with similar yields. I find that banks with tight regulatory constraints are significantly more likely to invest in these "misclassified" ABS. It seems that overrated ABS are not (or at least not only) bought by naive investors unaware of ratings inflation but by rational banks that pursue a regulatory arbitrage strategy.

Finally, I test the economic consequences of reaching for yield for banks. I find that constrained banks that reach for yield systematically buy the ABS with the lowest ex-post performance within each risk weight bucket. These ABS are backed by a significantly larger fraction of collateral that becomes delinquent nine months after investment than the ABS bought by unconstrained banks. At the same time, these ABS with worse collateral performance are not safer in other dimensions. For example, higher bond insurance or subordination levels do not overcompensate high delinquency rates. Overall, it seems that banks that arbitrage risk weights herd into the worst-performing ABS.[9]

My paper contributes a study of regulatory arbitrage on the *demand side* of the securitization market to the literature. To my knowledge, it is one of only five papers that use firm-level data on ABS holdings and the first paper to provide micro-level evidence for risk weight arbitrage by banks. Merrill et al. (2014), Chernenko et al. (2015), and Ellul et al. (2015) study insurance companies or mutual funds rather than banks. Merrill et al. (2014) find that life insurers exposed to losses from low interest rates in the early 2000s mostly invest in highly rated ABS. Chernenko et al. (2015) find that more seasoned fund managers and managers that personally experienced severe losses invest less into nonprime mortgages. Ellul et al. (2015) examine the interaction between historical cost accounting and capital regulation and its effects on the trading behavior of insurance companies in the ABS mar-

[8]Further reasons for low ratings accuracy in the securitization market include limited data availability, high asset heterogeneity and complexity, as well as "rating through the cycle" (for example, Cornaggia and Cornaggia, 2013).

[9]The use of yield spreads as a risk proxy is susceptible to mispricing, illiquidity, or feedback effects of regulatory arbitrage on yields. I stress that these are not valid concerns when looking at collateral delinquency rates because delinquency rates do not rely on prices.

ket.[10] Finally, Erel et al. (2014) estimate the ABS holdings of US banks using FR-Y9C data and show that investment in highly rated ABS correlates with securitization activity.

While the literature to date remains almost silent about the demand side of the securitization market, many papers have studied its supply side. For example, Calomiris and Mason (2004), Ambrose, LaCour-Little, and Sanders (2005), and Keys, Mukherjee, Seru, and Vig (2009) analyze regulatory arbitrage as an incentive for banks to move loans from their (regulated) balance sheets to (unregulated) off-balance sheet vehicles, which then securitize the loans. Acharya, Schnabl, and Suarez (2013) show that off-balance sheet asset-backed commercial paper conduits (ABCPs) allowed the sponsoring bank to reduce the regulatory capital required for the securitized collateral to nearly zero even though they provided very little risk transfer to the ultimate investors during the financial crisis.[11]

This paper also contributes to an academic debate about the question why investors bought ABS with biased credit ratings. Whereas some theories see "investor naivety" as an explanation (Blinder, 2007; Skreta and Veldkamp, 2009; Bolton, Freixas, and Shapiro, 2012), my empirical findings support the view that buying overrated ABS was an informed choice in pursuit of regulatory arbitrage benefits (Acharya and Richardson, 2009; Calomiris, 2009; Efing, 2015; Opp, Opp, and Harris, 2013).[12]

Finally, this paper is part of a larger literature that studies regulatory arbitrage in different asset classes, investor groups, or under different regulatory frameworks. Becker and Ivashina (2015) show that US insurance companies reach for higher corporate bond yields conditional on credit ratings. Acharya and Steffen (2015) find that equity returns of eurozone banks load positively on bond returns of south-European and Irish debt but negatively on German government bond returns. This "carry trade" behavior is more pronounced among banks with low capital ratios, which points to regulatory arbitrage and risk-shifting motives. Behn, Haselmann, and Vig (2014) and Plosser and Santos (2014) study the use of bank-internal credit ratings for regulatory purposes. Behn et al. (2014) use data from the German credit register to show that capital requirements decrease once their loans are regulated un-

[10] Also see Ellul, Jotikasthira, Lundblad, and Wang (2014).

[11] The provision of liquidity guarantees to ABCP conduits effectively allows recourse to the bank balance sheet but reduces the required capital to one-tenth of the capital required for on-balance sheet assets.

[12] According to the "regulatory arbitrage" hypothesis, investors readily buy ABS as long as inflated ratings sufficiently relax regulatory constraints. According to the "investor naivety" hypothesis, investors lack the expertise or find it prohibitively expensive to analyze the complex design of ABS and do not anticipate ratings inflation.

der the internal ratings-based approach. Plosser and Santos (2014) analyze data from loan syndicates and show that internal ratings are more biased if estimated by banks with tight regulatory constraints. Mariathasan and Merrouche (2014) provide similar evidence showing that weakly capitalized banks manipulate bank-internal credit ratings in countries with weak bank supervision.

The remainder of this paper is organized as follows. Section I reviews the Basel II Securitization Framework and shows evidence of the low yield-sensitivity of ABS risk weights. Section II states the theoretical predictions. The data set is described in Section III. Section IV presents the empirical findings, Section V shows robustness tests, and Section VI concludes.

I. Institutional Background

A. Basel II Securitization Framework

The Securitization Framework is part of the first pillar of Basel II, which regulates the minimum capital requirements for banks and was implemented by the European Union via the Capital Requirements Directive in 2006.[13] Germany incorporated the first pillar into national law through the Solvabilitätsverordnung (Solvency Regulation) published in mid-December 2006 and put into force in January 2007.

The key metric under the first pillar of Basel II is the capital adequacy ratio (CAR), which is defined as the ratio of eligible regulatory capital over risk-weighted assets and must be at least 8%. Risk-weighted assets are computed by multiplying each credit risk exposure of a bank by the appropriate risk weight and adding 12.5 times the capital requirements for operational and market risk. Two different approaches, the standardized approach (SA) and the internal ratings-based approach (IRB), are used to determine the appropriate risk weight for a given bank asset. Whether a bank must use the SA or the IRB approach for a securitization exposure depends on whether it would use the SA or the IRB approach for the type of underlying collateral securitized.

In general, credit ratings issued by external credit rating agencies are primarily used under the SA. By contrast, banks that are authorized to use the IRB approaches generally use their

[13]See directives 2006/48/EC and 2006/49/EC published on June 30, 2006.

own risk models to produce their ratings *internally*. However, the Basel II Securitization Framework is an exception to this rule. Even under the IRB approach the regulator obliges banks to use *external* credit ratings to determine ABS risk weights, mainly because the lack of statistical data for securitized products makes the production of meaningful internally generated ratings difficult (Basel Committee on Banking Supervision, 2009). The Basel II terminology, therefore, speaks of the IRB-RBA, where RBA is short for (external) ratings-based approach.[14] In short, banks under the SA *as well as* banks under the IRB(-RBA) must both use *external* credit ratings whenever available for a securitization exposure. This requirement makes the securitization market the ideal testing ground for the role of credit ratings in regulatory capital arbitrage.

Table I, column (1) shows how the ABS risk weights depend on (long-term) external credit ratings under the SA of the securitization framework. Credit ratings are pooled into rating categories such that, for example, AAA positions are multiplied with the same risk weight of 20% as AA- positions.[15] The mapping under the IRB-RBA approach (Table I, columns (2) to (4)) differs in two ways. First, the mapping is less coarse than under the SA and, for example, assigns an individual risk weight to AAA positions. Second, senior exposures receive lower risk weights and exposures backed by non-granular collateral pools receive higher risk weights relative to the base risk weight in column (3).[16]

B. Yield-Sensitivity of ABS Ratings and Capital Requirements

As credit ratings are strongly entrenched in ABS regulation, their performance as a risk benchmark has implications for financial stability. Becker and Ivashina (2015, p. 1863) point out that "imperfect benchmarks may create incentives to reach for yield in the context of fixed income investing or to reach for apparent alpha more generally. This could lead to excess risk-taking in financial institutions, a persistent distortion in investment, and,

[14]Under the securitization framework the IRB approach is divided into three (sub-) approaches. Among these, the ratings-based approach IRB-RBA (Table I, columns 2–4) is the most important because it must be applied to all securitization exposures that have an external credit rating. The two other (sub-) approaches, internal assessment approach and supervisory formula, must be applied when an external rating neither exists nor can be inferred. This paper analyzes only rated exposures.

[15]A similar mapping exists for short-term ratings but is ignored here as this paper only analyzes asset- and mortgage-backed securities that carry a long-term rating.

[16]Basel II.5 adds another distinction between securitization and resecuritization exposures. Banks were expected to comply with these revised requirements by December 31, 2011.

potentially, amplification of overall risk in the economy." Whether credit ratings are a useful risk benchmark for ABS regulation depends on the appropriate definition of risk.[17] As I analyze reaching for yield behavior, it seems natural to focus on risk that is priced by the market and to use yield spreads as a risk measure. The implicit assumption of this approach is that priced risk factors that are relevant for market participants should also be relevant for regulators.[18] I relax this assumption in Section IV.F where I focus on credit risk and use an alternative risk measure that does not rely on prices.

There are several reasons to believe that credit ratings for ABS are worse at measuring priced risk than ratings in many other debt classes. First, ABS exhibit relatively high systematic risk, which is likely to drive a large wedge between yield spreads and ratings/risk weights. Collin-Dufresne et al. (2012) show that ABS yield spreads capture systematic risk reasonably well whereas credit ratings are designed to capture physical default losses. Particularly low rating standards in the securitization market, partly due to moral hazard on the side of the agencies, constitute a second reason why ABS ratings tend to be less sensitive to risk than other credit ratings. Third, ABS are a heterogeneous asset class in terms of collateral, design, and complexity. This results in a large menu of ABS with different risk-return profiles in each rating bucket, which is likely to reduce the sensitivity of ABS ratings to priced risk further.

Figure 1 illustrates the weak relationship between yield spreads and ABS ratings. Graph (a) shows box plots for the yield spreads of 3,278 rated ABS that are issued as floating rate notes, at par, and between 2007 and 2012. The rating buckets are defined as in Table I, column (3) and mirror the base risk weights used under the IRB-RBA. A comparison of the different rating buckets reveals the significant dispersion of ABS yield spreads. While ABS with lower ratings tend to promise higher yield spreads, the relation is not strictly monotonic. For example, the median yield spread in the A+ bucket exceeds the median in the A- bucket and is only slightly lower than the median in the BBB+ bucket. The third quartile in the BB+ bucket is located above the third quartiles of the BB and the BB- buckets. The Pearson (Spearman) correlation between yield spreads and base risk weights

[17] The Basel framework does not provide a clear risk definition. For example, the definition of regulatory arbitrage in Basel Committee on Banking Supervision (1999) simply refers "true economic risk" without further specifying the meaning of this term.

[18] Yield spreads comprise several risk premia for different risk factors (e.g. credit risk, liquidity risk, etc.). Determining their identity and relative size would go beyond the scope of this paper.

(Table I, column (3)) is only 0.50 (0.53).

In Graph (b) of Figure 1 I draw new box plots after correcting the yield spreads for variation explained by different bond characteristics like nominal maturity, weighted average life, tranche size, ABS type dummies (RMBS, CMBS, CDO/CLO, other ABS) as well as for variation explained by time fixed effects and the level and slope of the term structure at the issuance date of the security.[19] While the median yield spread is now increasing from one rating category to the next, the yield-sensitivity of ratings remains low. Each rating bucket still comprises a large number of ABS whose yield spreads exceed even the median in the next lower rating category.

The low yield-sensitivity of ABS ratings offers banks large opportunities to reach for yield and to load on systematically risky ABS without incurring higher capital requirements. This is disturbing as the capital requirements for ABS are generally low. For example, an AAA rated ABS carrying the base risk weight of twelve percent would require only one Cent of equity for each Euro invested.[20] Figure 2 illustrates how these capital requirements, which are both very low and insensitive to yield spreads, allow banks to take highly leveraged positions that promise high returns on equity. For each ABS I compute the ratio between its yield spread and its capital requirement under the IRB-RBA (Table I, column (3)) to approximate its return on equity.[21] The box plots in Figure 2 show that banks can easily build positions that promise returns on equity of up to 70% (median in the A+ bucket) if they choose the highest possible leverage allowed by the regulator. Banks can achieve even higher returns on equity if they systematically buy the investment grade ABS with the highest yield spreads. The rest of this paper tries to answer the question to what extent banks really exploit these apparently large opportunities to reach for yield in the very asset class that was at the core of the financial crisis.

[19]See Section III for variable definitions.

[20]Capital requirements for an ABS investment are calculated as eight percent of the risk weighted investment size (see Section I.A). I.e. an investment of one Euro into an ABS with a base risk weight of twelve percent requires one Cent of equity ($\approx$ €1×0.12 × 0.08).

[21]For example, the return on equity promised by an ABS with a risk weight of twelve percent and a yield spread of thirty bps is approximated by $\frac{€1\times 0.30\%}{€1\times 0.12\times 0.08} = 31\%$. More generally: For a given capital requirement c per Euro invested, the return on equity is given as $\frac{(R_{Ref}+Spread)-(1-c)\times R_D}{c}$ where R_D denotes the cost of debt and R_{Ref} denotes the reference rate (e.g. Libor) that the ABS investment earns in addition to the yield spread. For $R_{Ref} \approx R_D$, the return on equity simplifies to $\left(\frac{Spread}{c} + R_{Ref}\right)$. For small R_{Ref} and c, this term equals approximately $\frac{Spread}{c}$.

II. Hypothesis Development

An important question is which banks arbitrage ABS risk weights most aggressively. From a financial stability perspective it would be problematic if especially the undercapitalized and presumably most fragile banks would evade regulation and herd into the systematically most risky ABS. Yet, there are several reasons to believe that this is indeed the case. For example, Boyson, Fahlenbrach, and Stulz (2016) find that riskier banks with tight regulatory constraints use trust-preferred securities to arbitrage Tier 1 ratios and Plosser and Santos (2014) show that constrained banks are more likely to bias internally generated risk weights. It seems likely that constrained banks are also using opportunities to arbitrage ABS risk weights.

Glasserman and Kang (2014) and Rochet (1992) show theoretically that reaching for yield is stronger for banks with binding regulatory constraints. They assume that a bank with risk aversion γ chooses to invest €x_i in security i so as to maximize

$$\max_{\mathbf{x}} \quad \mathbf{x}'\boldsymbol{\mu} - \frac{\gamma}{2}\mathbf{x}'\boldsymbol{\Sigma}\mathbf{x} \quad \text{s.t.} \quad \kappa \geq \mathbf{w}'\mathbf{x} \tag{1}$$

where $\boldsymbol{\mu}$ and $\mathbf{w}$ denote the vector of expected returns and the vector of risk weights and $\boldsymbol{\Sigma}$ denotes the covariance matrix of the investable securities.[22] The regulatory constraint in (1) limits risk-weighted assets $\mathbf{w}'\mathbf{x}$ to some level κ. For example, under Basel II κ equals 12.5 times eligible bank equity.[23] The solution to the optimization problem is given by

$$\mathbf{x} = \frac{1}{\gamma}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - \mathbf{w}\lambda) \quad \text{with} \quad \lambda = \frac{\mathbf{w}'\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} - \gamma\kappa}{\mathbf{w}'\boldsymbol{\Sigma}^{-1}\mathbf{w}} \ , \tag{2}$$

where λ is a scalar and larger than zero if the regulatory constraint is binding. If the constraint is not binding, the bank optimally invests $\frac{1}{\gamma}\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}$.[24] By contrast, if $\lambda > 0$, the binding constraint forces the bank to adjust investment by $\frac{-1}{\gamma}\boldsymbol{\Sigma}^{-1}\mathbf{w}\lambda$. In general, this adjustment changes the portfolio composition so that banks with binding regulatory constraints choose a different relative mix of securities than unconstrained banks. Only if risk weights are pro-

[22] Equation (1) shows the exact same model as in Glasserman and Kang (2014). Rochet (1992) additionally considers a short-selling constraint omitted here for simplicity.

[23] Under Basel II banks must have a capital adequacy ratio of at least 8% $\left(CAR = \frac{E}{\mathbf{w}'\mathbf{x}} > 8\%\right)$.

[24] Risk aversion ($\gamma > 0$) insures that an unregulated bank maximizes (1) at a finite level of leverage but does not affect the relative mix (portfolio weights) of the securities held by the bank.

portional to expected returns, regulation does not affect the relative mix of securities in the portfolio (Glasserman and Kang, 2014).[25]

For the general case Rochet (1992, p.1155) shows that constrained banks reach for yield and invest more into the securities for which the ratio μ_i/w_i is highest. The larger the variation in μ_i/w_i, the larger the predicted effect on the portfolio allocation of constrained banks. Therefore, as the yield-sensitivity of risk weights is particularly low for ABS (see Section I.B), I expect that reaching for yield in the ABS market is much more pronounced for constrained banks than for banks that are well capitalized in the eyes of the regulator.

Prediction: Reaching for Yield by Constrained Banks

> Banks with tight regulatory constraints exploit the low yield-sensitivity of ABS risk weights and reach for yield more aggressively than unconstrained banks.

Appendix A provides a detailed discussion of this prediction in a model that assumes the existence of three assets, two coarse risk weight categories, and a single-factor model for expected returns μ.

Note that the model does not explain why some banks are constrained by regulation and others are not. The parameter λ is endogenous.[26] Explaining why some banks are constrained and others are not is indeed important and I will address endogeneity concerns in the empirical part of this paper as best as possible. However, the focus of this paper is not on unravelling the endogeneity of regulatory constraints and banks' investment choices. The following analysis simply provides evidence that the constrained banks, which the regulator considers as most fragile, are indeed arbitraging ABS risk weights most aggressively. Furthermore, I will provide some indication of the magnitude of this arbitrage.

[25]For $\boldsymbol{w} = \alpha\boldsymbol{\mu}$ and some positive scalar α, the expected returns of all securities are reduced by the same factor, which has the same effect as increasing risk aversion γ (Glasserman and Kang, 2014, p. 1208).

[26]For example, Boyson et al. (2016) hypothesize that different business models explain why some banks operate with tight constraints and would like to take more risk than allowed by regulation.

III. Data

A. *German Bank Investments in Asset-Backed Securities*

The primary data set used in this study is the securities holdings statistics which allows me to examine the quarterly asset holdings of all commercial banks residing in Germany on a security-by-security basis since the introduction of Basel II in 2007. The data set is part of a centralized register of German security ownership across all major asset classes and investor groups and is maintained by the Deutsche Bundesbank. A detailed description of the data can be found in Amann, Baltzer, and Schrape (2012). I check bank ownership of 26,091 ABS for which I am able to find an ISIN identifier on Bloomberg or Dealogic. Roughly one half of this bond sample is European and the other half North American. Forty percent of the bonds are backed by residential mortgages and 46% were issued between 2006 and 2008. My analysis does not capture the ownership of securities not included in this sample. Therefore, reported investment volumes in this analysis should be considered as a lower bound.

The data set is limited to on-balance sheet holdings of ABS with an external credit rating. They reach their highest value in Q4.2009 and amount to €120bn. Unrated ABS or securitization exposures held in off-balance sheet vehicles do not show in the data set and would also require a different regulatory approach than the one discussed in Section I.A.[27] The size of German off-balance sheet holdings is lower than the on-balance sheet investments.[28] According to Arteta, Carey, Correa, and Kotter (2013, Table III), off-balance sheet holdings in securities arbitrage (SAVs), structured investment (SIVs), and hybrid vehicles sponsored by German banks amount to only US$ 102bn in Q2.2007.[29]

Figure 3 shows the German on-balance sheet holdings (nominal value) of ABS aggregated by bank type at the height of the financial crisis in December 2008. The holdings of the

[27]See Acharya et al. (2013) for an excellent study of regulatory arbitrage that targets off-balance sheet holdings in ABCPs in the USA. Unrated ABS are treated under the Supervisory Formula Approach.

[28]Erel et al. (2014) document that, also in the USA, off-balance sheet holdings of ABS are smaller than on-balance sheet holdings. On-balance sheet (off-balance sheet) holdings account for 5% (1.6%) of total assets for banks with more than US$ 1bn of trading assets and trading assets representing more than 10% of total assets.

[29]SAVs, SIVs, and hybrid vehicles are different types of (off-balance sheet) ABCPs. Multi-seller vehicles constitute another large segment of ABCPs but are not disclosed at the country level by Arteta et al. (2013). Contrary to the aforementioned ABCPs, multi-seller vehicles invest in short-term debt and, therefore, exhibit much lower maturity mismatches and systematic credit risk.

five biggest German banks and other commercial banks together account for roughly 70% of the German stock of ABS. They are followed by the Landesbanken (regional state banks that function as umbrella organizations for the savings banks) and the regional institutions of cooperative banks. The structured debt ownership of local savings and cooperative banks themselves is relatively small.

Figure 4 shows the composition of structured debt holdings on bank balance sheets as of December 2008 by asset type and national origin of the collateral. Eighty percent of bank investment in structured debt is backed by residential and commercial mortgages and 5% is collateralized debt and loan obligations. The remaining 15% is backed by a variety of collateral, like car and student loans. Fifty-eight percent of the collateral that is securitized and held on balance sheets originates in Germany followed by collateral pools of mixed national origin and by bonds backed by collateral from Spain and the UK. ABS backed by American collateral account for only 4% of *on-balance sheets holdings*. Off-balance sheet holdings of American ABS could be significantly larger, which would be consistent with Bertaut, DeMarco, Kamin, and Tryon (2012) who report large foreign purchases of US ABS.

B. *Constructing the Regression Sample*

As savings and cooperative banks are geographically limited in their scope of activities by law (Kick and Prieto, 2014) and hold almost no ABS (Figure 3), I drop them from the sample. I also eliminate banks with total assets less than €10bn as of March 2007 unless they are Landesbanken.[30] The final regression sample contains 58 banks that account for 65% of total German bank assets in March 2007. Two-thirds of these banks have each bought at least one ABS since December 2005. At the height of the structured debt crisis (December 2008) ABS amount to 1.5% of total assets for the average bank.

I expand the 58 banks by the ABS that are issued between 2007 and 2012, i.e. after the introduction of Basel II. For each bank-security pair I create a binary variable equal to 1 if the bank buys the security during the first six months after bond issuance. Focusing on trading days during the first six months after bond issuance is necessary for three reasons. First, banks sometimes move old bond holdings from an off-balance sheet vehicle to their balance sheets. In my data set this would look like a new bond purchase. By considering only

[30]The total sample comprises 2,113 banks including 1,807 cooperative banks, savings banks, and building societies, 243 banks with assets less than €10bn and five banks with unknown CAR.

young bonds acquired shortly after issuance, I rule out these false bond acquisitions. Second, I observe almost no secondary market trading by German banks which makes it difficult to obtain reliable time series data for yield spreads. Therefore, I concentrate on "fresh" ABS acquisitions for which I can use the prices and yield spreads reported at issuance. Third, my data set only shows "launch" credit ratings published at the date when a bond is issued but not any subsequent rating changes. Focusing on trading days during the first six months is not a serious limitation. I still capture 82% of the entire investment volume.[31]

The analysis uses yield spreads to proxy priced risk of ABS. I follow He et al. (2012) and define the yield spread "as the fixed markup in bps over the reference rate specified at issuance (e.g. the one-month Libor rate)." To make yield spreads comparable, I restrict the bond sample to the 3,278 floating rate notes that are issued at par and denoted in Euros.[32] In Section IV.F I show that my results also hold if these filters are not applied and I use an alternative risk measure (collateral delinquency rates) that does not rely on yields. To limit the influence of data outliers, which might be simple reporting errors, I winsorize the yield spreads at the 1st and 99th percentile of the distribution. Finally, 1,097 ABS lack data on one or more control variables and are dropped. The probit regressions used in Section IV suppress another 297 bonds with credit ratings that perfectly predict the failure of the outcome variable. The final bond sample contains 1,884 ABS of which 57% are backed by mortgages, 13% are collateralized debt and loan obligations, and the remaining bonds are backed by a variety of collateral. The final regression sample (banks expanded by bonds) has 102,239 observations.

C. Summary Statistics

Table II, Panel A reports summary statistics for the 58 banks at the trading dates of the 1,884 bonds in the final regression sample.[33] The average bank has total assets worth €92.4bn but bank size exhibits considerable variation with a standard deviation of €123.6bn.

The capital adequacy ratio (CAR), defined as eligible regulatory capital over risk-weighted

[31] Investment volume is calculated using the market price at the time of investment.

[32] Focusing on bonds denoted in Euros loses only the 4% of on-balance sheet holdings that account for ABS with American collateral (Figure 3).

[33] If a bank buys a given bond (within six months after issuance), I report the values of the bank variables at the reported date of bond purchase. If a bank does not buy a given bond, I report the values of the bank variables at the next bank reporting date following the date of bond issuance.

bank assets, equals on average 15% and has a standard deviation of 6%. The 10th percentile equals only 10%, which means that a considerable number of observations has a CAR close to the regulatory minimum requirement of 8%. The blue solid line in Graph (a) of Figure 5 shows that the average CAR is steadily increasing, i.e. that regulatory constraints are relaxing, throughout the sample period.

Comparing the CARs of banks to their unweighted leverage ratios (defined as equity over total assets) provides some interesting insights. The average leverage ratio equals only 4% and is thus almost four times smaller than the sample mean of the CAR. The difference between both variables is even more striking at the 10th percentile, which equals only 1.4% for the leverage ratio and is seven times smaller than for the CAR. Considering their low capital cushions, it seems that German banks are more susceptible to even relatively small losses in their asset portfolios than other institutional investors. The red dashed line in Graph (a) of Figure 5 shows that the leverage ratios of German banks are, on average, increasing between 2007 and 2010. After 2010 the average leverage ratio first stagnates and then decreases again—unlike the average CAR. The correlation between the leverage ratio and the CAR equals only 0.16, which illustrates that the unweighted leverage ratio is a bad measure for the tightness of the regulatory constraint.

Table II, Panel B reports bond characteristics at issuance for the 1,884 ABS in the final regression sample. All ABS are issued at par. Their yield spreads have a sample average of 100bps and a standard deviation of 109bps. Graph (b) of Figure 5 shows that the average yield spread of AAA rated ABS is increasing over the sample period. The nominal maturity for the average bond is 34 years whereas the weighted average life is only 6.1 years.[34] Bond size is defined as the face value of the ABS and on average €514m. Launch credit ratings published by Moody's, Standard & Poors and Fitch are aggregated into one composite rating. If the security has two ratings, the more conservative rating is used. If the security has three ratings, the median rating is chosen.[35] Forty-seven percent of the bonds carry a AAA rating, only 4% carry a composite rating below investment grade (Table II, Panel C). Finally, I extract US Libor rates from the Thomson Reuters Datastream to construct

[34]According to Firla-Cuchra (2005), the weighted average life is a more meaningful maturity measure than the nominal maturity due to structured cash-flows and embedded prepayment options of ABS.

[35]This aggregation approach is required by the Basel Securitization Framework in cases where more than one eligible credit rating agency can be used and these assess the credit risk of the same securitization exposure differently (Basel Committee on Banking Supervision, 2006).

proxies for the shape of the term structure at the time of bond issuance (Table II, Panel D). *Term Structure Level* represents the one-month Libor rate and measures the level of the term structure, whereas *Term Structure Slope* is the difference between the 12-month Libor and the one-month Libor rate and proxies the slope of the term structure.

D. Comparing ABS Bought by Constrained and Unconstrained Banks

I compare the ABS bought by banks with lagged CARs above and below 10%. CARs below 10% are close to the regulatory minimum threshold of 8% and signify a relatively tight constraint. I use the one-quarter lag of CARs as each ABS purchase mechanically alters the risk weighted assets and, thereby, the contemporaneous CAR of the investing bank. Table III shows that unconstrained banks (lagged CAR $> 10\%$) buy ABS with an average yield spread of 68bps. By contrast, banks with a (lagged) CAR $\leq 10\%$ buy ABS with an average yield spread of 153bps. The difference of 86bps is statistically significant at the 1% level both in a t-test and in a Wilcoxon rank-sum test. On average, banks with low CARs buy riskier ABS.[36]

In a second step I compare the average capital requirement for ABS bought by constrained and unconstrained banks.[37] Unconstrained banks buy ABS with an average capital requirement of 1.79 Cent per Euro invested whereas banks with lagged CARs below 10% are required to hold, on average, 3.33 Cent of equity for each Euro invested. Finally, I compute the ratio between the yield spread and the capital requirement to approximate the return on equity promised by an ABS.[38] I find that the average ABS bought by an unconstrained bank promises a return on equity of 47.06% if the bank chooses the highest possible leverage allowed by regulation. By contrast, the average ABS bought by a constrained bank with a CAR close to the minimum threshold promises a return on equity of 73.74%.

In summary, Table III suggests that constrained banks buy ABS with higher priced risk than unconstrained banks. The higher risk is not accompanied by a proportional increase in capital requirements. This allows constrained banks to build positions that promise an on average 26.68% higher return on equity than the ABS bought by unconstrained banks.

[36]Considering only *AAA* rated bond purchases, I find that banks with a lagged CAR $\leq$ 10% buy *AAA* rated ABS with an, on average, 22bps higher yield spread than banks with CARs above 10%. The difference is significant at the 5% level.

[37]The capital requirement for an investment of one Euro equals €1 $\times$ risk weight $\times$ 0.08 (see Section I).

[38]See Section I.B and Footnote 21 for details of this approximation.

This result provides first evidence that constrained banks exploit the low risk-sensitivity of rating contingent regulation and reach for yield in the ABS market. However, the result is derived from a purely non-parametric analysis which does not control for unobserved ABS and bank heterogeneity. Moreover, Table III only compares ABS that are actually purchased and ignores information from ABS that banks decide not to buy. In the following sections I will estimate linear and non-linear probability models that explain why banks are more likely to buy certain ABS and not others.

IV. Results

A. *Risk Weight Arbitrage at the Extensive Margin*

I begin by estimating the extensive margin of investment and model the conditional probability of security acquisition. The binary variable $I_{b,s}$ equals 1 if bank b invests into ABS s, otherwise $I_{b,s} = 0$. The probability $\Pr(I_{b,s} = 1)$ is parametrized to depend on an index function $\beta\mathbf{X}$, where $\mathbf{X}$ is a $K \times 1$ regressor vector of bank and security characteristics and β is a vector of unknown parameters:

$$P(I_{b,s} = 1|\mathbf{X}) = \Phi(\beta\mathbf{X}) \tag{3}$$

The cumulative distribution function $\Phi(.)$ can be specified in several ways. Following Ellul et al. (2015), I estimate linear probability models and simply regress the dummy $I_{b,s}$ on $\beta\mathbf{X}$ in Table IV. Using ordinary least squares regressions (OLS) has the advantage that regression coefficients can directly be interpreted as marginal effects on the probability that bank b buys ABS s.

Column (1) of Table IV only reports the coefficient of the ABS yield spread *Spread*, which captures yield seeking in banks' investment decisions. The effect of *Spread* is conditioned on *RWC*, which is a vector of dummies for the different Basel II risk weight categories of securities.[39] The yield spread, hence, only captures risk taking *inside* risk weight buckets while the vector *RWC* absorbs any risk shifting *across* different risk weight categories. The positive coefficient of *Spread* equal to 0.028% suggests that banks indeed reach for yield.

[39] Appendix B explains how the risk weight categories *RWC* are identified in the data.

The model in column (2) of Table IV allows reaching for yield to vary across banks with different capital adequacy ratios (CARs). As in Section III.D, I lag CARs by three months to address reverse causality concerns. The interaction *Lag CAR*×*Spread* in column (2) allows for the possibility that banks with different CARs have different propensities for yield seeking. Similarly, the interaction *Lag CAR*×*RWC* allows for the possibility that banks with different *Lag CAR* have diverging preferences for different risk weight buckets. The coefficient of *Lag CAR*×*Spread* is negative and significant at the 1% level. The evidence shows that especially constrained banks with low CARs reach for yield and arbitrage ABS risk weights.

In column (3) of Table IV I include a vector of bond variables that control for ABS heterogeneity. Besides time fixed effects, I include the level and the slope of the term structure at the exact day of bond issuance to ensure that yield spreads of ABS are comparable across time (see Section III.C). The vector *ABS Controls* further includes controls for the nominal maturity and the weighted average life, the (log) size of the ABS tranche, as well as dummy variables for the different ABS types (RMBS, CMBS, CDO/CLOs, other ABS). As the ABS bought by banks with low CARs might be systematically different from the ABS purchased by unconstrained banks, I also include interaction terms between the ABS controls and *Lag CAR*. Even after including these different bond controls, I observe a negative and highly significant coefficient for *Lag CAR*×*Spread*.

In column (4) I control for bank but not for bond heterogeneity. *Log Assets* and its interactions with *Spread* and *RWC* are included as large banks could have different incentives to reach for yield due to too-big-to-fail subsidies, higher sophistication, lower transaction costs, or different business models. More importantly, column (4) includes bank fixed effects so that identification only relies on comparing the purchase decisions of a given bank as its CAR changes over time. Therefore, slow-moving bank characteristics with little time variation like, for example, bank business models, governance culture, or market expertise are unlikely to provide alternative explanations for reaching for yield. The coefficient of *Lag CAR*×*Spread* remains negative and significant at the 5% level in column (4).

In column (5) I estimate the full OLS specification with controls for bond as well as bank heterogeneity. Again, the coefficient of *Lag CAR*×*Spread* remains negative and significant at the 5% level. However, unlike in column (4), the coefficient of *Log Assets*×*Spread* becomes highly significant. This is consistent with several studies that document more aggressive regulatory arbitrage for large banks, too. For example, Acharya et al. (2013) find that exposure to ABCPs correlates with bank size. A possible explanation could be that large too-big-to-fail banks have higher incentives for regulatory arbitrage because increasing risk maximizes the value of their public bail-out guarantees (Carbo-Valverde, Kane, and Rodriguez-Fernandez, 2013). Especially ABS with high systematic risk would be attractive investments for too-big-to-fail banks because these ABS typically default only during economic crises when the probability that systemic banks are bailed out is highest (Coval et al., 2009).

In column (6) I estimate the same specification as in column (5) but standard errors are clustered by bank and by ABS deal. Clustering by bank seems important as the ABS choices of a given bank might be correlated due to some characteristics specific to the bank. I cluster standard errors also by ABS deal because the different ABS tranches in a deal share common deal characteristics like, for example, the day of issuance, documentation, etc. Column (6) shows that double clustering does not change the evidence for reaching for yield by constrained banks. If anything, *Lag CAR*×*Spread* has a lower standard error than in column (5).

The linear probability models reported in Table IV have important shortcomings. In particular, they suffer from the conceptual flaw that probabilities can be outside the interval $[0, 1]$. The OLS specifications appear to fit the data poorly. The R^2 is as low as 0.003 in column (1) and never exceeds 0.021. Therefore, I additionally estimate two probit models in Table V.[40] I include the same independent variables and interaction terms as in Table IV, columns (5) and (6). In particular, both probit models include the vector of dummy variables *RWC* for the different risk weight categories and the interactions *Lag CAR*×*RWC* and *Log Assets*×*RWC*. However, bank fixed effects are only controlled for in the second probit model. The pseudo R^2 of 0.230 and 0.282 suggest that the two probit models without and with bank fixed effects fit the data much better than the linear probability models. A Hosmer-Lemeshow specification test cannot reject the null hypothesis that the two probit models are correctly specified.[41]

[40]The estimated marginal effects are almost identical if I use a logit or complementary log-log specification (see Section V). The probit specification is chosen here because it has the highest log pseudolikelihood.

[41]The Hosmer-Lemeshow specification test divides the sample into five subgroups. Within each subgroup, the test compares the sample frequency of the dependent variable to the predicted probability. I also rerun the test with 10 or 20 subgroups, which does not change the test outcome.

Column (1) of Table V shows the coefficient estimates of the probit model without bank fixed effects. Unlike the linear probability model, the probit model does not allow a direct interpretation of these regression coefficients as marginal effects, which are defined as

$$\frac{\partial P(I_{b,s}=1|\mathbf{X})}{\partial x_j} = \phi(\beta\mathbf{X}) \cdot \beta_j \ . \tag{4}$$

As the marginal effect in equation (4) depends on the the independent variables $\mathbf{X}$ in the (normal) density term $\phi(\beta\mathbf{X})$, it is customary in the literature to compute the average marginal effect:[42]

$$\widehat{AME}_j = N^{-1} \sum_i \phi(\hat{\beta}\mathbf{X}_i) \cdot \hat{\beta}_j \tag{5}$$

Column (2) of Table V shows the average marginal effects of the independent variables *Spread*, *Lag CAR*, and *Log Assets* in the probit model without bank fixed effects. The ABS yield spread has an average marginal effect of 0.096% on the probability of security acquisition and is statistically significant. Conditional on the risk weight categories *RWC*, an increase of the spread by one percentage point increases the probability of security acquisition by 34% relative to the sample average (=0.279%).

The estimation of the interaction effects *Lag CAR*×*Spread* and *Log Assets*×*Spread* requires additional attention as neither the sign nor the statistical significance of the regression coefficients have a clear interpretation in a probit model (Ai and Norton, 2003). In the literature, different approaches have emerged to estimate and illustrate interaction effects in non-linear models (see Karaca-Mandic, Norton, and Dowd, 2012). I calculate and plot the marginal effect of *Spread* at different values of *Lag CAR* and *Log Assets* (see, for example, Williams, 2012; Canette, 2013; StataCorp., 2013).[43]

Graph (1) of Figure 6 illustrates the interaction effect *Lag CAR*×*Spread* in the probit model without bank fixed effects. The vertical axis shows the average marginal effect of *Spread* on the purchase probability for different values of *Lag CAR* on the horizontal axis. Clearly, a higher yield spread does not significantly increase the probability that uncon-

[42]See Cameron and Trivedi (2005). Average marginal effects are calculated using the *margins* command with the *dydx*-option in Stata. Confidence intervals are calculated with the delta method.

[43]Alternatively, one could compute the cross-partial derivative of the conditional probability with respect to the two interacted variables (Ai and Norton, 2003; Norton, Wang, and Ai, 2004). A disadvantage of the cross-partial derivative is that all information is condensed into one number. By contrast, the approach chosen in this paper allows to compare the average marginal effect of *Spread* at different values of *Lag CAR*.

strained banks with *Lag CAR* above 16% buy the ABS. By contrast, the average marginal effect of *Spread* becomes statistically significant for banks with a low *Lag CAR* and is highest for banks at the regulatory 8%-floor. An increase of the yield spread by one percentage point increases the probability that a bank with a *Lag CAR* of 8% buys an ABS in a given risk weight bucket by 0.229%, and thus almost doubles the purchase probability relative to the sample average (= 0.279%). As predicted in Section II, banks with tight regulatory constraints are more likely to buy the ABS with the highest yield spreads in a given risk weight category. The effect disappears for unconstrained banks operating far away from the 8% minimum requirement.[44] Similarly, Graph (2) shows that larger banks are more likely to reach for yield than small banks.

In Model II of Table III I estimate a probit model with bank fixed effects. In non-linear models with *short* panels, joint estimation of firm fixed effects and regression coefficients can lead to an incidental parameter problem (Greene, 2004). However, as each bank fixed effect is based on almost 2000 (bond-)observations, this concern should be greatly alleviated in this analysis. Still, the fixed effects regressions should be interpreted with caution as the probit dropps 35 banks whose fixed effects perfectly predict the value of the outcome variable $I_{b,s}$. Modell II only describes reaching for yield in a subsample of 23 banks.

The interaction effect *Spread* × *Lag CAR* becomes much stronger if bank fixed effects are controlled for. Figure 6, Graph (3) shows that the average marginal effect of *Spread* at a *Lag CAR* of 8% increases to 1.279% and is more than five times larger than in Model I (compare Graph (1)). The average marginal effect of *Spread* decreases very fast at low values of *Lag CAR* corroborating the evidence that incentives to arbitrage risk weight categories are strongest close to the 8%-floor.[45] By contrast, Figure 6, Graph (4) shows that the interaction effect *Spread* × *Log Assets* becomes insignificant once bank fixed effects are included. This is not surprising as bank size varies little over time. Overall, controlling for bank heterogeneity strengthens the evidence that constrained banks reach for yield more than unconstrained banks.

It is interesting to ask which risk weight categories are arbitraged most aggressively. Figure 2 in Section I.B suggests that reaching for yield should be most profitable for highly

[44]The marginal effects at different values of *Lag CAR* are significantly different from zero and from each other. See Appendix C, Table C.1.

[45]The statistical significance of the differences between the average marginal effects of *Spread* at different *Lag CAR* is shown in Appendix C, Table C.1.

rated ABS because they promise particularly high yield spreads relative to their risk weights. Figure 7 confirms this prediction. Graph (1) of Figure 7 is based on the probit model without bank fixed effects and plots the average marginal effect of the yield spread by rating bucket. As predicted, constrained banks reach for yield more aggressively in the investment grade rating buckets. This observation is confirmed in Graph (2) which is based on the second probit model with bank fixed effects.

B. *Risk Weight Arbitrage at the Intensive Margin*

The previous subsection analyzed the extensive margin of ABS investment. This approach has the disadvantage that it treats two bond acquisitions the same even if investment volumes are very different. To address this concern, I use the Euro-amount invested in ABS s by bank b as the dependent variable in this section. I scale investment size of ABS s by total investment in ABS by bank b:

$$\textit{Standardized InvVol}_{b,s} = \frac{InvVol_{b,s}}{\sum_{i \in \Omega(b,s)} InvVol_i} \cdot 100\% \tag{6}$$

where $\Omega(b,s)$ is the set of all ABS bought by bank b in the same year-quarter as ABS s.

As *Standardized InvVol* is left-censored at zero, I estimate Tobit regressions. Simple OLS regressions and robustness checks for the *Log Standardized InvVol* are reported in Appendix D. The regression coefficients and average marginal effects of a Tobit model without bank fixed effects are reported in Table VI, columns (1) and (2).[46] Its pseudo R^2 suggests that it describe the data reasonably well. Graph (1) in Figure 8 illustrates the negative interaction effect *Lag CAR* × *Spread*. An increase of the bond yield spread by one percentage point increases the fraction of capital invested in the ABS by about 1% for a bank operating with a CAR at the regulatory 8%-floor. The average marginal effect of the yield spread decreases for higher CARs and becomes statistically insignificant for *Lag CAR* $\geq$ 16%. This observation is confirmed by the tobit model with bank fixed effects in columns (3) and (4) of Table VI and its corresponding Graph (2) in Figure 8. Constrained banks invest a larger share of their portfolio into ABS that promise a high yield spread relative to their risk weight.

[46]The marginal effects are computed for the left-truncated mean ($\partial E[y|x, y > 0]/\partial x$). The control variables and interactions are the same as in Table IV, columns (5) and (6). In particular, I include dummies for risk weight categories *RWC* and the interactions *Lag CAR* × *RWC* and *Log Assets* × *RWC*.

C. Regulatory Arbitrage versus Agency Problems

Low bank capitalization has the dual effect of tightening a bank's regulatory constraint and possibly exacerbating agency conflicts between creditors and shareholders (Jensen and Meckling, 1979; Admati et al., 2011, e.g.). In this section I analyze whether agency problems (e.g. risk shifting) alone are enough to explain the risk weight arbitrage documented in Section IV. We might imagine that, even in the absence of regulation, highly leveraged banks with more pronounced agency conflicts would choose the high-yield securities in a group of ABS with the same credit rating. To test this idea I replace the regulatory metric *Lag CAR* by the leverage ratio, defined as equity over total *unweighted* assets. Both variables are only weakly correlated (see Section III.C). Therefore, the leverage ratio should do poorly at capturing tight regulatory constraints but still do a good job at capturing agency problems. If the latter alone could explain risk weight arbitrage, we would expect a strong interaction effect *Spread* × *Leverage Ratio*.

I rerun Model I from Table V using the leverage ratio instead of *Lag CAR*. Figure 9, Graph (1) shows that a marginal increase of *Spread* significantly increases the probability of security acquisition across the entire interval of the leverage ratio. However, the graph is flat, showing no differences between banks with low and high leverage suggesting that incentives for reaching for yield arise due to low levels of *regulatory* capital rather than low leverage ratios per se. Figure 9, Graph (2) shows the interaction effect *Spread* × *Leverage Ratio* if I control for bank fixed effects. At low values of the leverage ratio a marginal increase of *Spread* seems to increase the purchase probability by more than at higher values of the leverage ratio. However, the difference is never statistically significant at the 5% level. Graphs (1) and (2) suggest that only tight regulatory constraints and not bank leverage alone can explain the risk weight arbitrage documented in Section IV.A.

D. Quantifying Regulatory Arbitrage

The evidence presented so far suggests that precisely the banks that the regulator considers weakly capitalized and most fragile try to avoid higher capital requirements for systematically risky ABS. From a regulatory perspective, it is important to know the magnitude of this regulatory arbitrage. This section addresses the following questions: How much riskier are the ABS bought by constrained banks that reach for yield? How much does risk weight arbitrage allow constrained banks to evade higher capital requirements? What is the combined effect of higher asset risk and higher leverage on the profitability of constrained banks' ABS investments?

Figure 10 shows the average yield spread (interpreted as a proxy for priced risk), capital requirement per Euro invested, and promised return on equity of ABS bought by banks with different CARs. Instead of comparing the actual values reported in Table III, I analyze the values predicted by the probit model specified in column (1) of Table V.[47] This approach has the advantage that the predicted yield spreads and capital requirements are corrected for bond heterogeneity captured by the control variables in the probit model and that the predicted values reflect information both from actual ABS acquisitions as well as from ABS that banks refuse to buy.

The decreasing red solid line in Figure 10 clearly shows that constrained banks buy riskier ABS with, on average, higher yield spreads than unconstrained banks with high CARs. If the regulatory framework was working effectively, the riskier ABS investments of constrained banks should be associated with higher capital requirements. Yet, this is not the case. On the contrary, the blue dashed line representing the average capital requirement per Euro invested is upward sloping. Banks with tight regulatory constraints incur lower capital requirements than unconstrained banks although they load more on systematic risk priced by the market.

For example, a bank with a *Lag CAR* equal to 20% buys ABS with a capital requirement of, on average, 7.2 Cent per Euro invested and a yield spread of 87bps. By contrast, a bank with a low *Lag CAR* equal to 9% (and, hence, a tighter regulatory constraint) buys ABS with a risk weight of, on average, only 2.4 Cent per Euro invested but a high yield spread of 112bps. The three times lower capital requirement together with the higher yield spread translates into a roughly four times higher return on equity promised by the average ABS position of the constrained bank ($\approx$ 46.39% / 12.15%).[48] Under the assumption that a four times higher return on equity reflects a significant increase in the risk of the position, the Basel Securitization Framework does not appear to constrain banks' risk choices in the ABS market effectively.

[47] See Appendix E for details on how the coefficient estimates from the probit model are used to compute the average yield spreads and capital requirements of ABS bought by banks with different CARs.

[48] The return on the equity promised by both positions is approximated as $\frac{€1 \times 1.12\%}{€0.024}$ and $\frac{€1 \times 0.87\%}{€0.072}$, respectively. See Section I.B and Footnote 21 for a discussion of this approximation.

E. *Ratings Inflation and Risk Weight Bias*

Constrained banks buy ABS that are, on average, riskier but have lower capital requirements than the ABS bought by unconstrained banks. This apparent mismatch is possible because the relation between ABS ratings and yield spreads is not monotonic (see Section I.B). In each rating bucket r there exists a considerable number of ABS whose yield spreads exceed even the average yield spread in the next lower rating bucket $r+1$ (see Figure 1). These securities are misclassified in the sense that they have lower risk weights but (much) higher yield spreads than other ABS. This section provides evidence that constrained banks with low CARs systematically buy these misclassified ABS.

For each security in a given RWC r I compute the difference between its yield spread and the average spread in the next lower RWC $r+1$. I call this difference the *Risk Weight Bias* and set it to zero if it is negative. The *Risk Weight Bias* is thus computed as a *directed* classification error that is positive only when yield spreads are too high relative to their risk weights.[49] Table VII shows that the regression coefficients and average marginal effects of *Risk Weight Bias* are positive and statistically significant. In a group of ABS with the same risk weight category RWC banks are more likely to buy the misclassified securities. Graphs (3) and (4) of Figure 9 show that the average marginal effect of *Risk Weight Bias* decreases monotonically over *Lag CAR* in regression specifications without (Graph 3) and with bank fixed effects (Graph 4).[50] Constrained banks systematically buy misclassified ABS with too low risk weights. They seem to benefit from the fact that credit rating agencies sometimes inflate ABS ratings and at least partly ignore systematic risk reflected in ABS yields.

F. *Implications of Regulatory Arbitrage*

Risk weight arbitrage can endanger financial stability if it allows excessive risk taking by institutional investors. Securitization exposures appear particularly dangerous in this regard for two reasons. First, even relatively small ABS portfolios can pose a significant risk to investors as losses in the ABS market tend to realize at the same time and during

[49] As in Graph (b) of Figure 1, the yield spreads are corrected for variation explained by the nominal maturity, weighted average life, (log) tranche size, and ABS type of the securities, as well as for variation explained by time fixed effects, and the level and slope of the term structure at the issuance date. See Appendix F for details.

[50] I report OLS regressions for this result in Appendix Table H.1.

economic downturns. Second, low liquidity suggests that it is difficult for investors to sell securitization exposures again when they are in distress. Both, high systematic risk and low liquidity make ABS a potentially more dangerous investment for banks than for most other institutional investors. Their particularly low capital buffers provide only a thin cushion to absorb losses and maturity transformation makes them more susceptible to illiquidity risk than, for example, insurance companies.[51]

To evaluate the implications of risk weight arbitrage for German banks empirically, I compare the performance of ABS bought by banks that arbitrage risk weights and by banks that do not reach for yield. Analyzing the performance of ABS positions seems preferable to comparing overall bank performance which is typically determined by numerous and potentially unobservable bank characteristics besides a bank's securitization exposures. As an ex post performance measure for ABS positions I use the 90 days-delinquency rate measured nine months after ABS issuance/acquisition. Moody's database "Performance Data Services"reports the delinquency rates of 1,529 ABS.[52] High delinquency rates signify low collateral performance and high credit risk.[53]

The analysis in Table VIII asks whether the ABS bought by constrained banks that reach for yield perform worse than other securities in the same risk weight category. The two probit models differ from the specifications in previous sections in two ways. First, the independent variable *Spread* is replaced by the delinquency rate. Second, I also control for the combined face value of subordinated deal tranches that serve as a loss cushion to a given security in an ABS deal, a dummy variable equal to 1 if the ABS has bond insurance, and the number of tranches in the deal of the ABS. These additional ABS controls mitigate concerns that bad collateral performance (high delinquency rates) is compensated by different kinds of credit

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[51]As banks were unable to liquidate their securitization exposures in the market, governments allowed banks to transfer toxic assets to public "bad banks". In Germany, the Federal Parliament (Bundestag) approved a bill enabling the creation of bad banks in 2009.

[52]See Appendix G for details of the delinquency data. As the delinquency analysis does not rely on yield spreads, I do not need to restrict the sample to ABS denoted in the same currency, issued at par and as floating rate notes.

[53]I stress that the computation of delinquency rates does not rely on prices. Hence, this section also serves as a useful robustness check to address concerns about illiquidity or mispricing. For example, Stanton and Wallace (2013) provide evidence that there are feedback effects of regulation on the prices of highly rated commercial mortgage-backed securities (CMBS). In this paper, regulation might have a feedback effect on yields because constrained banks systematically buy the high-yield bonds in each risk weight category, thereby driving up their prices. This would reduce arbitrage benefits and lower incentives to reach for yield. Yet, a similar feedback effect would not affect delinquency rates.

enhancement.

Columns (1) and (2) of Table VIII report the coefficients and average marginal effects of a probit specification without bank fixed effects. *Delinquency* has a statistically significant average marginal effect of -0.030%. An increase of the delinquency rate by one standard deviation (= 2.10%) reduces the probability that the bank buys the ABS by 0.063%, which corresponds to a reduction by 33% relative to the sample average (= 0.192%). On average, banks are less likely to buy ABS that will perform badly nine months after issuance. The results are qualitatively similar in the second probit model with bank fixed effects.

Figure 9, Graph (5) shows the interaction effect *Lag CAR* × *Delinquency*. The average marginal effect of *Delinquency* decreases monotonically in the lagged CAR. It is zero for banks at the regulatory minimum of 8% but becomes negative and statistically significant for *Lag CAR* above 11%.[54] Banks operating with CARs close to the regulatory minimum buy ABS with high and low ex post performance with approximately equal probability. By contrast, banks with high CARs only buy ABS with relatively low delinquency rates nine months after acquisition. Graph (6) shows a similar result for the probit model with bank fixed effects except that the average marginal effect of *Delinquency* becomes positive for low lagged CARs.[55] In summary, constrained banks that reach for yield also allocate a larger portfolio share to ABS that will perform badly ex post.[56]

V. Robustness

I estimate a battery of alternative regression models for the probability that a bank buys a given ABS. Table IX, columns 2 and 4 report the average marginal effects of *Spread*, *Lag CAR*, and *Log Assets* in a logit and a complementary log-log model, respectively. The reported values are very close to the average marginal effects shown for the corresponding probit specification in Table V, column 2.[57] Figure 11 shows that the interaction effects

[54]The difference between the average marginal effect at a *Lag CAR* of 8% and average marginal effects at values of *Lag CAR* above 17% is significant with p-values between 0.09 and 0.03 (one-sided test).

[55]The difference between the average marginal effect at *Lag CAR* equal to 8% and at higher CARs is significant with p-values between 0.08 and 0.02 (one-sided test).

[56]I report OLS regressions for this result in Appendix Table H.1.

[57]The different regression coefficients in the probit, logit, and complementary log log model are due to different scaling. The log pseudolikelihood is slightly higher for the probit specification used in Section IV (−1509.2) than for the logit (−1511.6) and the complementary log-log model (−1511.9).

Lag CAR × *Spread* estimated in the logit and complementary log-log model are almost identical to the probit estimate illustrated in Figure 6, Graph (1). Furthermore, I also find robust evidence for reaching for yield if the regression sample is limiting to only *AAA* rated ABS (see Appendix Figure D.1). The results presented in Section IV.A are also robust to controlling for banks' total ABS holdings, the amount of collateral that the bank securitizes itself, and the amount of derivatives trading in the probit model.[58]

Finally, I check the robustness of the Tobit regressions for investment volumes. In Appendix D, I replace the *Standardized Investment Volume* by its logarithmic transform, which reduces the non-normality of the dependent variable in the sample of positive values. I also rerun the volume-regressions using ordinary least squares regressions instead of Tobit specifications. The results remain qualitatively unchanged (see Appendix D).

VI. Conclusion

Credit ratings are deeply enshrined in bank regulation. Yet, if ratings do not distinguish between idiosyncratic risk and systematic risk factors priced by the market, regulation can undercharge banks for investments with high systematic risk (Iannotta and Pennacchi, 2012). The securitization market constitutes a suitable testing ground for this hypothesis thanks to the particularly low yield-sensitivity of ABS ratings and its relevance for financial stability.[59]

Exploiting micro data on securitization exposures, this study shows that banks do indeed arbitrage rating-contingent regulation and reach for yield in the very asset class that was at the core of the financial crisis. Especially banks with tight regulatory constraints buy the ABS with the highest yields and systematic risk in a group of securities with the same risk weight. This result suggests that reaching for yield is mainly motivated by regulatory arbitrage considerations (Rochet, 1992; Glasserman and Kang, 2014). To ensure robustness, I directly examine plausible alternative explanations. Agency problems, bank size, or time-invariant bank characteristics like business models or bank sophistication alone are unlikely to explain why only constrained banks reach for yield inside risk weight categories.

The extent of regulatory arbitrage is economically significant. The ABS investments

[58] These variables might be interpreted as proxies for banks' expertise in the ABS market.

[59] Note that the European Commission (2015) is aiming at reviving the European securitization market to stimulate lending to the real economy.

of banks that reach for yield promise a return on regulatory capital approximately four times higher than the ABS bought by banks that do not arbitrage risk weights. This large magnitude is in part due to the inflation of external credit ratings and justifies regulatory reform. Under the Basel III Securitization Framework external credit ratings published by agencies will be replaced by internal credit ratings produced by the banks themselves (Basel Committee on Banking Supervision, 2014). However, whether these internal ratings will be more sensitive to priced risk is questionable. Evidence from the loan market suggests that moral hazard can impede the production of informative ratings by banks (Behn et al., 2014; Plosser and Santos, 2014). An alternative approach would be to calibrate risk weights to market measures of risk (Rochet, 1992).

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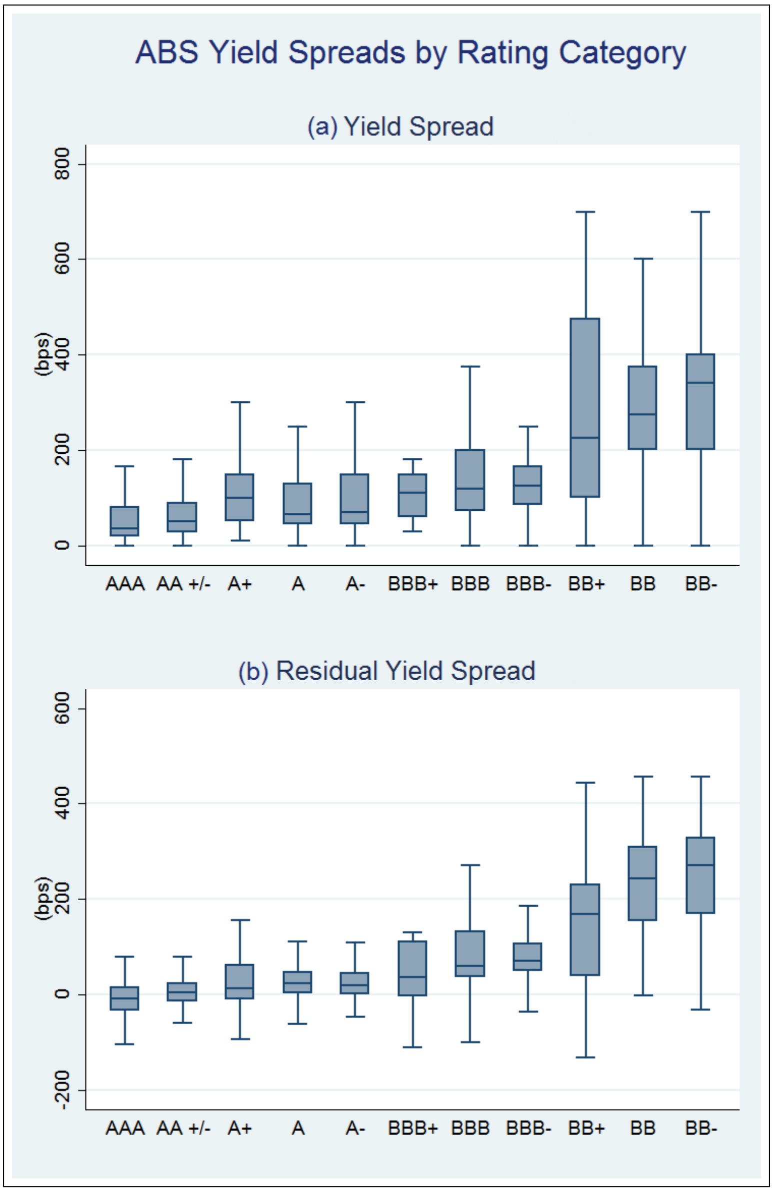

Figure 1. ABS yield spreads by rating category. Shown are box plots for the yield spreads of 3,278 asset-backed securities issued as floating rate notes, at par, and between 2007 and 2012. The yield spread in Graph (a) is defined as the fixed markup in bps over the reference rate specified at issuance (e.g. the one-month Libor rate). The residual yield spread in Graph (b) is defined as the yield spread corrected for variation explained by the nominal maturity, the weighted average life, the (log) tranche size, and the ABS type of the security, as well as for variation explained by time fixed effects and by the level and slope of the term structure at the issuance date of the security. The bottom and the top of the box plots are the first and third quartiles, the band inside is the median, and the ends of the whiskers are the lowest and highest values still within 1.5 times the inter-quartile range.

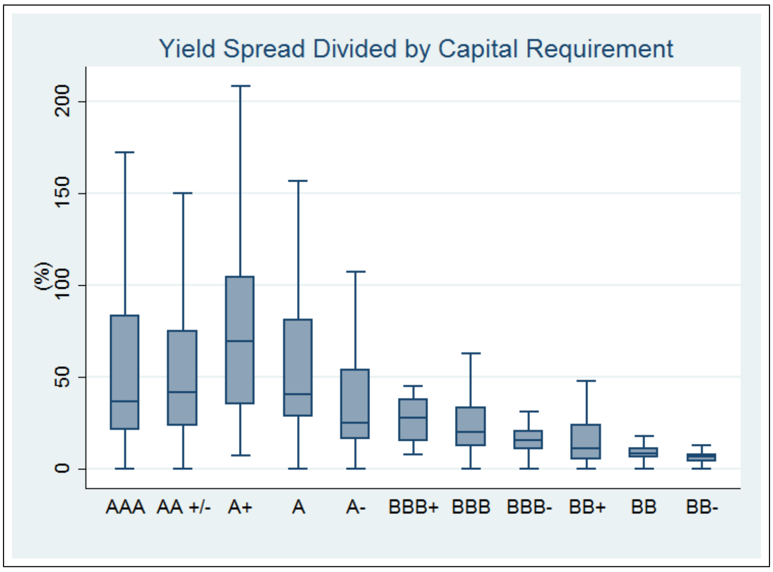

Figure 2. Promised return on equity by rating category. Shown are box plots for the returns on equity promised by 3,278 asset-backed securities issued as floating rate notes, at par, and between 2007 and 2012. The return on equity promised by an ABS is approximated by its yield spread divided by the regulatory capital requirement for an investment of one Euro under the IRB-RBA (Table I, column (3)). The bottom and the top of the box plots are the first and third quartiles, the band inside is the median, and the ends of the whiskers are the lowest and highest values still within 1.5 times the inter-quartile range.

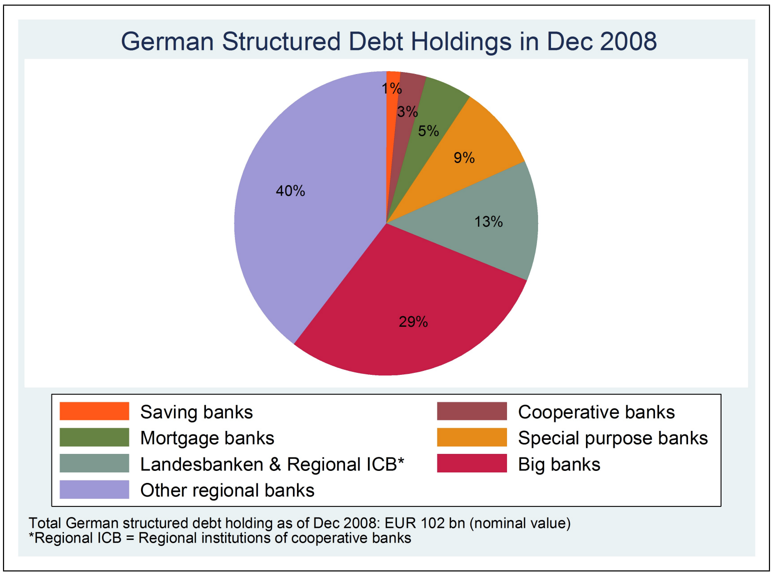

Figure 3. German structured debt holdings by bank category. Shown are the German on-balance sheet holdings (nominal value) of asset-backed securities as of December 2008 aggregated by bank category. Total structured debt holdings as of December 2008 equal €102bn.

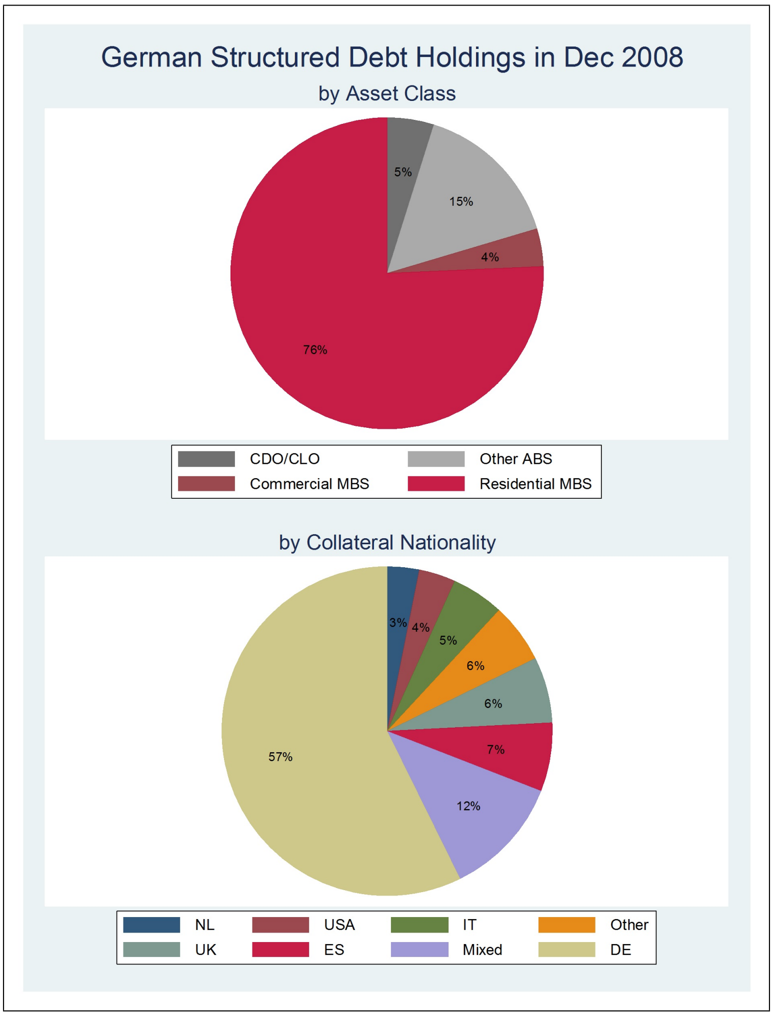

Figure 4. Asset type and national origin of German structured debt holdings. Shown is the composition of on-balance sheet structured debt holdings by German banks as of December 2008 by asset type and national origin of the collateral. Total German structured debt holdings as of December 2008 equal €102bn. The country abbreviations are: NL: Netherlands, USA: United States, IT: Italy, UK: United Kingdom, ES: Spain, Mixed: Mixed collateral origin, DE: Germany.

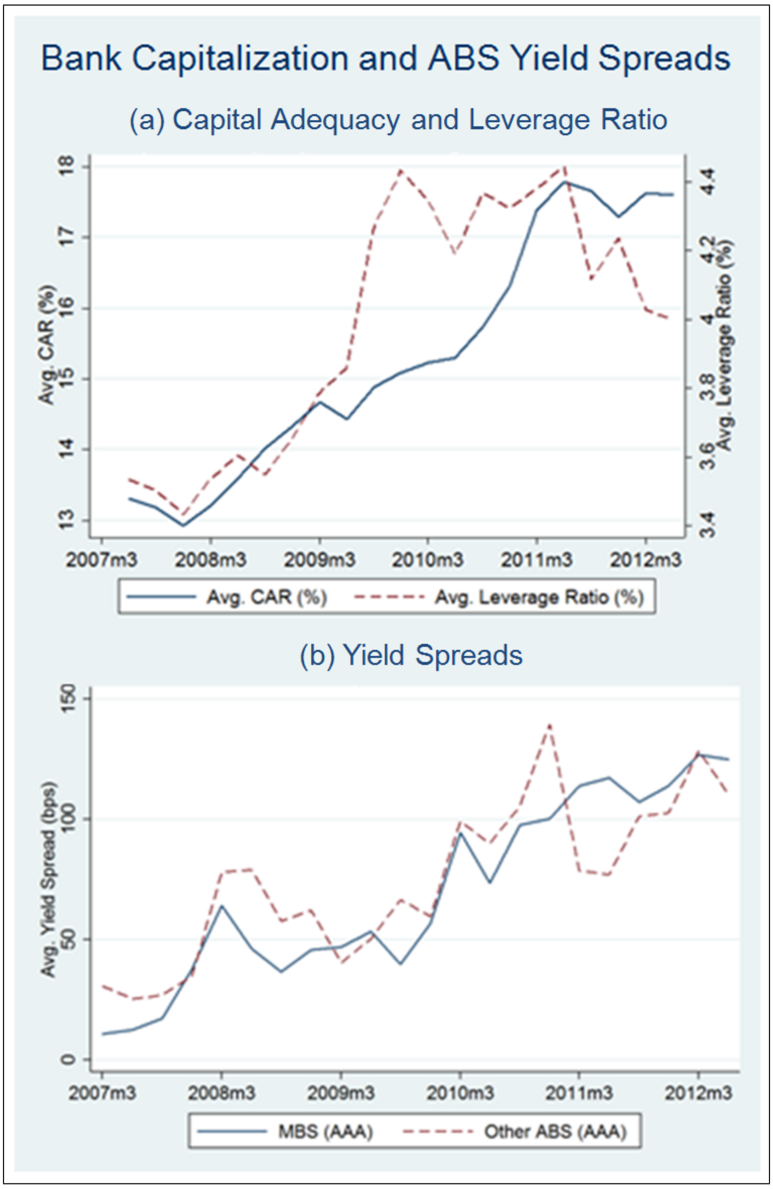

Figure 5. Bank capitalization and ABS yield spreads over time. Graph (a) shows the capitalization of the 58 largest banks in Germany between 2007 and 2012. The blue solid line shows the average capital adequacy ratio as defined in the Basel II framework. The red dashed line shows the average leverage ratio defined as equity over total assets. Graph (b) shows the average yield spread of AAA rated mortgage-backed securities (blue solid line) and other asset-backed securities (red dashed line) that are issued as floating rate notes, at par, and between 2007 and 2012.

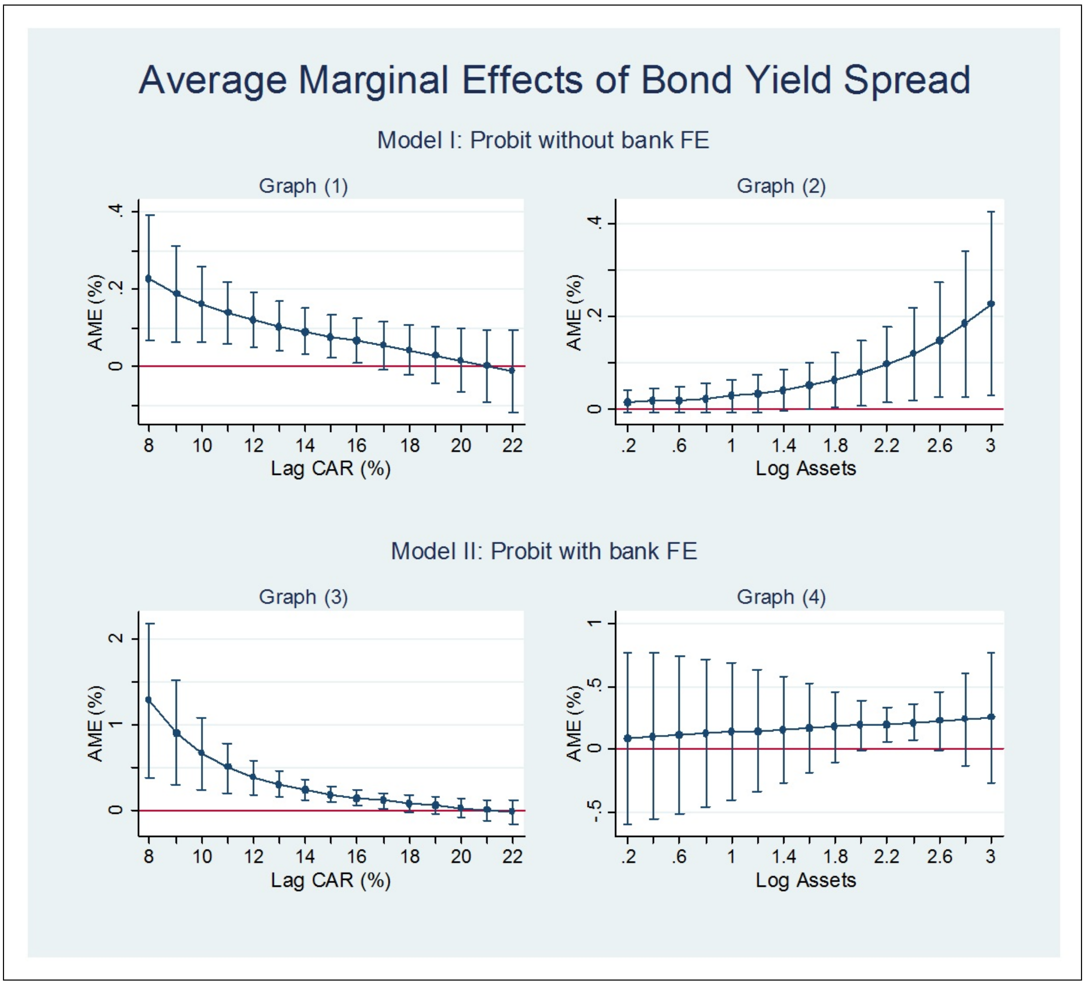

Figure 6. Probability of ABS acquisitions in probit regressions. Graphs (1)–(4) illustrate whether banks with low capital adequacy ratios and large banks are more likely to buy the high-yield bonds in a group of ABS with the same risk weight. The vertical axis shows the average marginal effect of the bond yield spread on the probability that a bank with given *Lag CAR* or *Log Assets* buys the ABS. The horizontal axes show different values for the three-months lag of the CAR (median = 14%, 90th percentile = 22%) and *Log Assets* (median = 1.43%, 90th percentile = 3.17%). Graphs (1) and (2) illustrate the interaction effects *Spread* × *Lag CAR* and *Spread* × *Log Assets* estimated in Table V, Model I (without bank fixed effects). Graphs (3) and (4) correspond to Table V, Model II (with bank fixed effects). Confidence intervals are drawn for the 5% level.

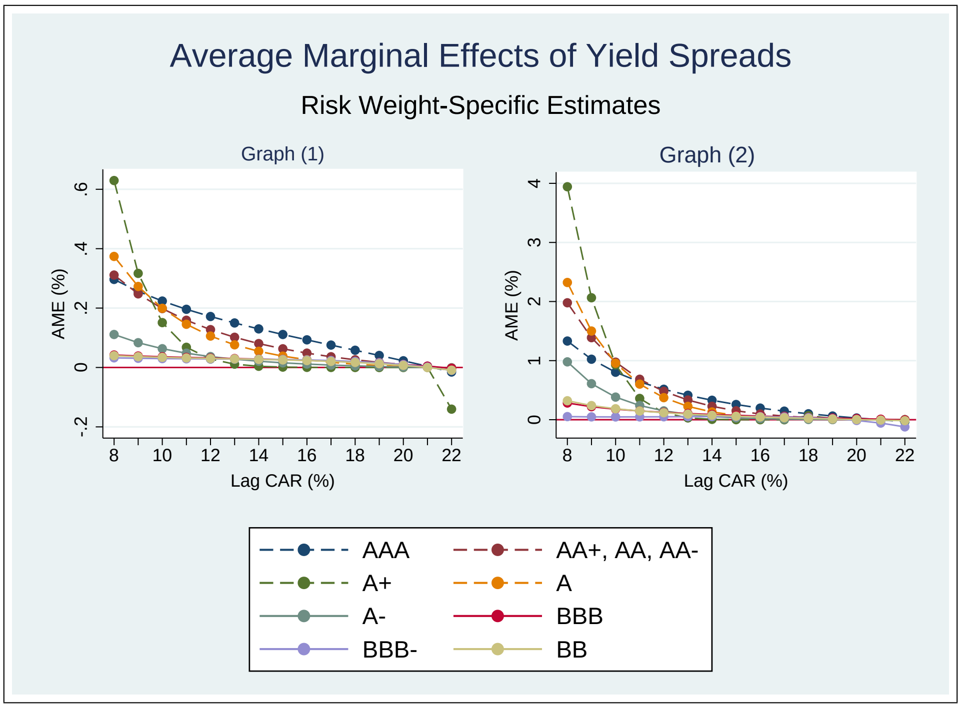

Figure 7. Reaching for yield by risk weight category. The graph shows the *RWC*-specific estimates for reaching for yield. Average marginal effects of the yield spread are estimated for different values of *Lag CAR* and risk weight categories with different ratings. The estimates in Graph (1) are computed using Table V, Model I without bank fixed effects. Graph (2) is estimated using Table V, Model II with bank fixed effects.

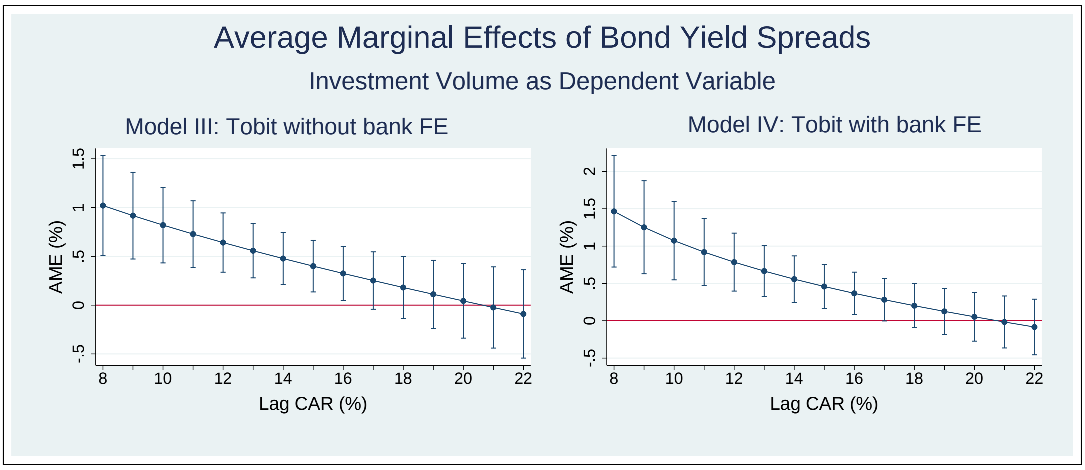

Figure 8. Investment volumes in Tobit regressions. Both graphs show the average marginal effect of the bond yield spread on the (standardized) investment volume defined as the Euro-amount invested in the ABS as a fraction of total ABS investments by the bank. Model III is estimated without bank fixed effects and Model IV with bank fixed effects. Confidence intervals are drawn for the 5% level.

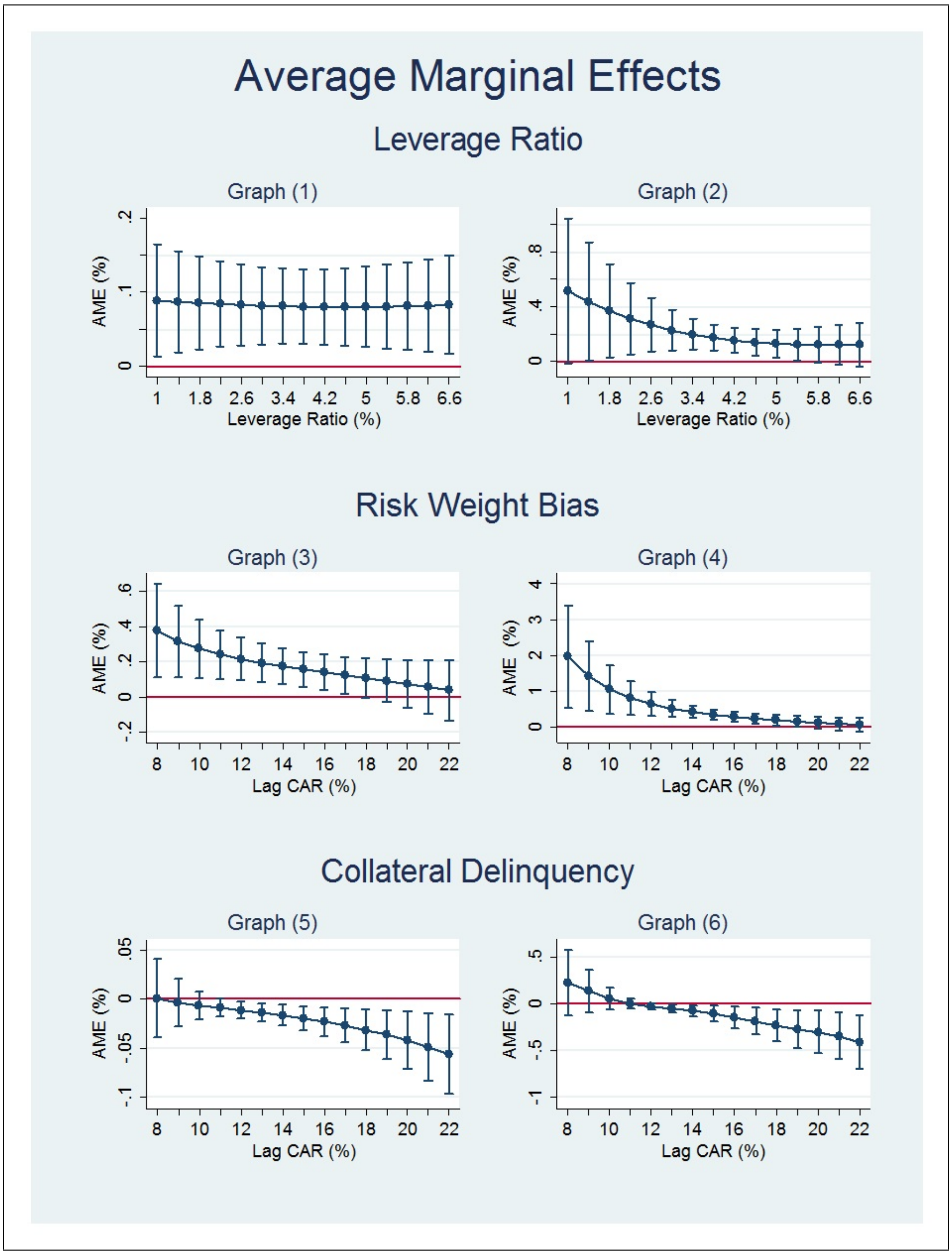

Figure 9. Bond purchase decisions, leverage, risk weight bias, and collateral delinquency. Graphs (1) and (2) show the average marginal effect of the bond yield spread on the probability that a bank with given *Leverage Ratio*, defined as book equity over total assets, buys the ABS. Graphs (3) and (4) show the average marginal effect of the *Risk Weight Bias* on the probability that a bank with given *Lag CAR* buys the ABS. Graphs (5) and (6) show the average marginal effect of the delinquency rate of bond collateral on the probability that a bank with given *Lag CAR* buys the ABS. Only Graphs (2), (4) and (6) come from regressions that control for bank fixed effects. Confidence intervals are drawn for the 5% level.

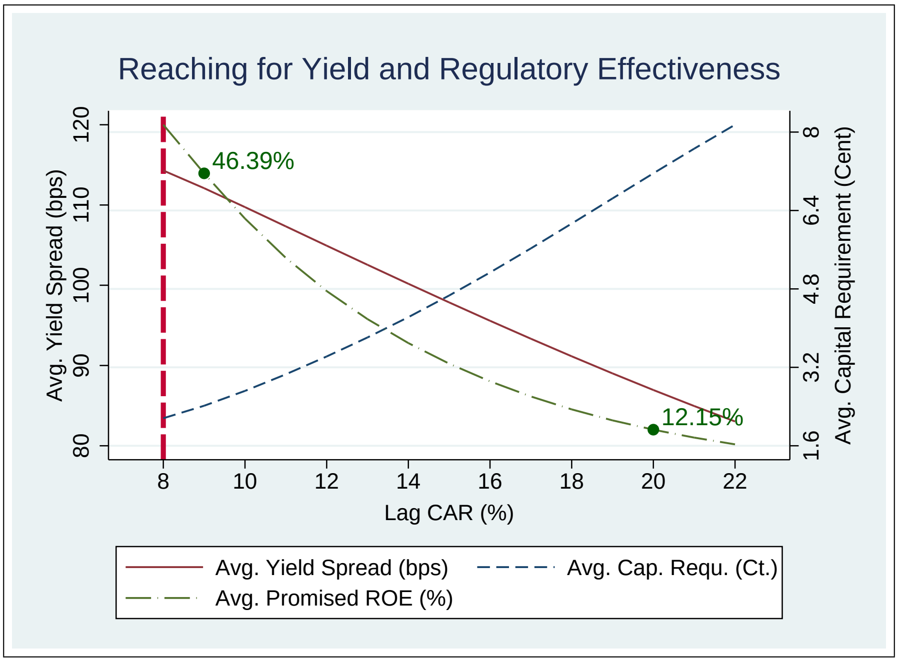

Figure 10. Reaching for yield and regulatory effectiveness. I use the coefficients in column (1) of Table V to predict the average yield spread (red solid line) and the average regulatory capital requirement per Euro invested (blue dashed line) of ABS bought by banks with lagged CARs equal to 8, 9, ..., 22% (see Appendix E for details). The green dashed-dotted line represents the return on equity promised by the ABS and is calculated as the ratio between the predicted yield spreads and capital requirements.

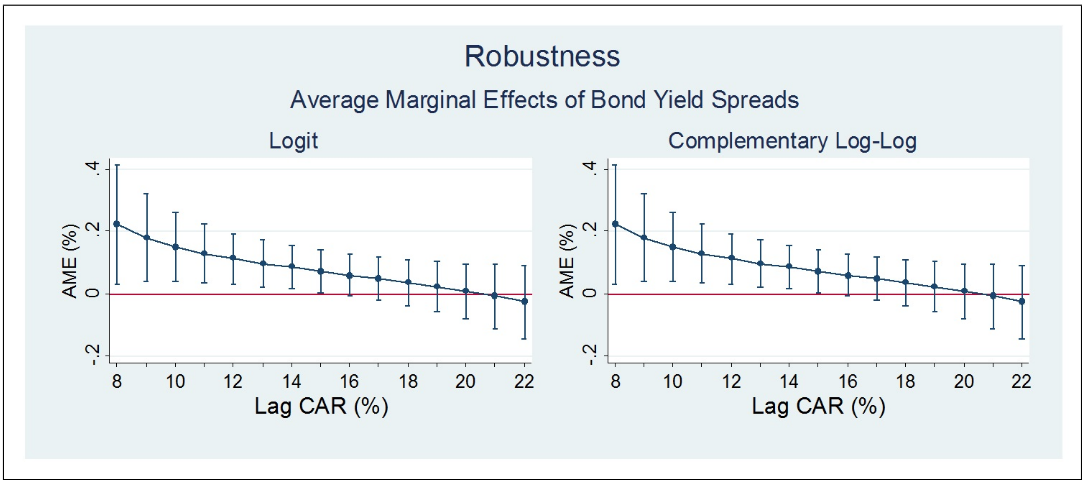

Figure 11. Robustness to logit and complementary log-log specifications. The two graphs show the average marginal effect of the bond yield spread on the probability that a bank with given *Lag CAR* buys the ABS. Neither the logit nor the complementary log-log specification controls for bank fixed effects. Confidence intervals are drawn for the 5% level.

Table I
Credit Ratings in the Basel Securitization Framework

Reported are the appropriate Basel II risk weights for securitization exposures with different long-term credit ratings published by external credit assessment institutions (ECAIs). Column (1) shows the risk weights applied under the Basel standard approach (SA) whereas columns (2) to (4) show the risk weights for the internal ratings-based approach for securitization exposures that carry an external credit rating (IRB-RBA). Unrated positions and assets carrying a rating below *BB-* are not assigned a risk weight but require deductions from eligible regulatory capital. The risk weights shown for the IRB-RBA are relevant if a bank would use the IRB for the underlying (unsecuritized) loan type and if the security carries an external credit rating.

	SA	IRB-RBA		
External rating (long-term)	Risk weight (1)	Senior position (2)	Base risk weight (3)	Non-granular Collat. Pools (4)
AAA	20%	7%	12%	20%
AA+	20%	8%	15%	25%
AA	20%	8%	15%	25%
AA-	20%	8%	15%	25%
A+	50%	10%	18%	35%
A	50%	12%	20%	35%
A-	50%	20%	35%	35%
BBB+	100%	35%	50%	50%
BBB	100%	60%	75%	75%
BBB-	100%	100%	100%	100%
BB+	350%	250%	250%	250%
BB	350%	425%	425%	425%
BB-	350%	650%	650%	650%
Below *BB-*	Deduction	Deduction	Deduction	Deduction
Unrated	Deduction	Deduction	Deduction	Deduction

Table II
Summary Statistics

Panel A summarizes bank characteristics at the issuance dates of the bonds in the sample. Panels B and C report summary statistics on the bond characteristics of 1,884 ABS. Panel D reports summary statistics on the term structure at the issuance dates of the bonds in the sample. Only banks with total assets worth more than €10bn, Landesbanken and central banks of cooperative banks are considered. Cooperative banks themselves, savings banks and building societies are excluded. All bonds are floating rate notes paying the Libor or the Euribor as base rate plus a spread (winsorized at 1% in each tail), are denominated in Euros and issued at par. Forty-nine percent of the bonds are residential mortgage-backed securities and the remaining 51% are ABS with other types of collateral. All bonds are issued between 2007 and 2012 with 68% being issued during the first two years. The countries where most collateral comes from are Spain (37%), the Netherlands (14%), United Kingdom (14%), Germany (13%), Italy (9%), other European countries (11%), and the USA (2%).

Variable	Description	Obs	Mean	Std. Dev.	Q10	Median	Q90
A. Bank Characteristics							
Total Assets	Total Assets in €10bn	1,109	9.24	12.36	1.25	4.16	23.84
Log Total Assets	Log(*Log Total Assets*)	1,109	1.58	1.13	0.22	1.43	3.17
CAR	Capital Adequacy Ratio	1,103	0.15	0.06	0.10	0.14	0.22
Lag CAR	*CAR* lagged by 3 months	1,109	0.15	0.06	0.10	0.14	0.22
Leverage Ratio	*Equity/Assets*	1,109	0.04	0.03	0.01	0.04	0.07
B. Bond Characteristics							
Yield Spread	To Euribor or Libor (%)	1,884	1.00	1.09	0.16	0.60	2.2
Issuance Price	In % of face value	1,884	100	0	100	100	100
Nominal Maturity	At issuance in years	1,884	34.2	18.3	10.2	36.7	52.6
Weighted Avg. Life	At issuance in years	1,884	6.1	4.1	1.8	5.2	11.2
Bond Size	Face value in US$	1,884	514m	1,211m	14m	104m	1,303m
Log Bond Size	Log(*Bond Size*)	1,884	4.80	1.80	2.60	4.64	7.17
Risk Weight Bias	See Eq. (F2), (in %)	1,884	0.18	0.48	0.00	0.00	0.54
C. Composite Rating Dummies							
AAA	1 for ratings shown	1,884	0.47	-	-	-	-
$AA+/AA/AA-$	1 for ratings shown	1,884	0.11	-	-	-	-
$A+/A/A-$	1 for ratings shown	1,884	0.20	-	-	-	-
$BBB+/BBB/BBB-$	1 for ratings shown	1,884	0.18	-	-	-	-
$BB+/BB/BB-$	Rating below *BBB-*	1,884	0.04	-	-	-	-
D. Term Structure at Bond Issuance (in %)							
Term Structure Level	1mth Libor	1,884	2.91	2.17	0.25	2.72	5.32
Term Structure Slope	12mth minus 1mth Libor	1,884	0.42	0.63	−0.32	0.16	1.40

Table III
ABS Acquisitions of Unconstrained and Constrained Banks

Compared are the average ABS bought by unconstrained (lagged CAR > 10%) and constrained banks (lagged CAR ≤ 10%). Columns (1) and (2) report the average *Yield Spread*, *Capital Requirement* = capital required per Euro invested, and *Spread / Capital Requirement* = ratio of bond yield spread and capital requirement per Euro invested. Column (3) reports the differences in means of the three variables. Column (4) reports the standardized test statistic for a two-sample t-test. Column (5) reports the standardized test statistic for the null hypothesis of a Wilcoxon rank-sum test that the ABS purchased by unconstrained banks are distributed like the ABS bought by constrained banks.

Average ABS bought by banks with CAR $\lesseqgtr$ 10%	Lagged CAR		Difference test		
	> 10%	≤ 10%	Diff	t-stat	z-stat Wilcoxon
	(1)	(2)	(3)	(4)	(5)
Yield Spread	0.678%	1.534%	-0.856%	-4.630***	-4.887***
Capital Requ. per Euro	0.018€	0.033€	-0.015€	-2.055**	-6.043***
Spread / Cap. Requ.	47.06%	73.74%	-26.68%	-3.202***	-4.258***

Table IV
Probability of ABS Acquisition in OLS Regressions

I use OLS regressions to estimate the marginal effects of various bank and ABS characteristics on the probability that a bank buys a given ABS (reported in %). The dependent variable is 1 if the bank purchases the bond and zero otherwise. The independent variables are: *Spread* = yield spread of ABS (floating rate note); *Lag CAR* = capital adequacy ratio lagged by three months; and *Log Assets* = $Log(Bank\ Assets)$. The set of ABS controls contains the following variables: *Nominal Maturity* = nominal bond maturity; *WAL* = weighted average life; *Log Bond Size* = $Log(Bond\ Face\ Value)$; *Term Structure Level* = one-month Libor rate at bond issuance; and *Term Structure Slope* = difference between 12-months and one-month Libor rate at bond issuance. All specifications control for time fixed effects and binary indicator variables for the different risk weight categories *RWC*. Some specifications control for asset type and/or bank fixed effects. All specifications include a constant. Robust standard errors are reported in parentheses. They are clustered by bank and by ABS-deal in column (6). The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively.

Dep. Variable: *Purchase Yes/No*	(1)	(2)	(3)	(4)	(5)	(6)
Spread	0.028*	0.100***	0.188***	0.042	0.034	0.034
	(0.016)	(0.036)	(0.043)	(0.039)	(0.045)	(0.031)
Lag CAR		2.218***	0.623	2.547**	-0.552	-0.552
		(0.575)	(2.184)	(1.077)	(2.206)	(4.897)
Lag CAR × Spread		-0.504***	-0.625***	-0.393**	-0.447**	-0.447**
		(0.191)	(0.228)	(0.192)	(0.227)	(0.199)
Log Assets				0.367***	-1.982***	-1.982***
				(0.105)	(0.275)	(0.668)
Log Assets × Spread				0.026	0.081***	0.081**
				(0.020)	(0.023)	(0.034)
ABS Controls:	No	No	Yes	No	Yes	Yes
Fixed Effects:						
RWC	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Asset Type	No	No	Yes	No	Yes	Yes
Bank	No	No	No	Yes	Yes	Yes
Interactions:						
Lag CAR × RWC	No	Yes	Yes	Yes	Yes	Yes
Lag CAR × Time	No	Yes	Yes	Yes	Yes	Yes
Lag CAR × ABS Controls	No	No	Yes	No	Yes	Yes
Lag CAR × Asset Type	No	No	Yes	No	Yes	Yes
Log Assets × RWC	No	No	No	Yes	Yes	Yes
Log Assets × Time	No	No	No	Yes	Yes	Yes
Log Assets × ABS Controls	No	No	No	No	Yes	Yes
Log Assets × Asset Type	No	No	No	No	Yes	Yes
N Observations	102,239	102,239	102,239	102,239	102,239	102,239
N Banks	58	58	58	58	58	58
N Bonds	1,884	1,884	1,884	1,884	1,884	1,884
R^2	0.003	0.003	0.005	0.017	0.021	0.021
Double-clustered s.e.	No	No	No	No	No	Yes

Table V
Probability of ABS Acquisition in Probit Regressions

Reported are regression coefficients and average marginal effects (in %) of probit estimations. The dependent variable is 1 if the bank purchases the bond and zero otherwise. Only Model II controls for bank fixed effects. Otherwise, the independent variables, fixed effects, and interactions are the same as in Table IV, columns (5) and (6): *Spread* = yield spread of ABS (floating rate note); *Lag CAR* = capital adequacy ratio lagged by three months; and *Log Assets* = *Log*(*Bank Assets*). The set of ABS controls contains the following variables: *Nominal Maturity* = nominal bond maturity; *WAL* = weighted average life; *Log Bond Size* = *Log*(*Bond Face Value*); *Term Structure Level* = one-month Libor rate at bond issuance; and *Term Structure Slope* = difference between 12-months and one-month Libor rate at bond issuance. All specifications control for time and asset type fixed effects and for binary indicator variables for the different risk weight categories *RWC*. All specifications include a constant. Standard errors are reported in parentheses and clustered by bank. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively. The p-value of the Hosmer-Lemeshow goodness-of-fit test is reported for five groups (H0: probit correctly specified).

	Model I Without Bank FE		Model II With Bank FE	
	Coeff	AME	Coeff	AME
Dep. Variable: *Purchase Yes/No*	(1)	(2)	(3)	(4)
Spread	0.375***	0.096***	0.399***	0.238***
	(0.134)	(0.037)	(0.142)	(0.067)
Lag CAR	−5.056	−0.285	8.567	−8.321
	(7.985)	(1.411)	(20.286)	(5.668)
Lag CAR × *Spread*	−2.085***		−2.659***	
	(0.793)		(0.847)	
Log Assets	−1.860***	0.266***	−3.278***	−0.088
	(0.418)	(0.097)	(0.802)	(1.052)
Log Assets × *Spread*	0.026		0.059**	
	(0.021)		(0.028)	
ABS Controls and Interactions:	Yes	Yes	Yes	Yes
Fixed Effects:				
RWC, Time, Asset Type	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes
N Observations	102,239	102,239	41,988	41,988
N Banks	58	58	23	23
N Bonds	1,884	1,884	1,884	1,884
Pseudo R^2	0.230	0.230	0.282	0.282
Hosmer-Lemeshow GoF (p-value)	0.469	0.469	0.519	0.519

Table VI
Investment Volumes in Tobit Regressions

The dependent variable is the standardized investment volume defined as the Euro-amount invested in ABS s by bank b as percentage of the aggregated Euro-amount that bank b invests into all ABS purchased in the same year-quarter. Columns 1 and 2 report the regression coefficients and the average marginal effects of a Tobit specification without bank fixed effects. Columns 3 and 4 report the regression coefficients and the average marginal effects of a Tobit specification with bank fixed effects. Average marginal effects are computed for the investment volume truncated at zero. The independent variables, fixed effects, and interactions are the same as in Table IV, columns (5) and (6): *Spread* = yield spread of ABS (floating rate note); *Lag CAR* = capital adequacy ratio lagged by three months; and *Log Assets* = *Log*(*Bank Assets*). The set of ABS controls contains the following variables: *Nominal Maturity* = nominal bond maturity; *WAL* = weighted average life; *Log Bond Size* = *Log*(*Bond Face Value*); *Term Structure Level* = one-month Libor rate at bond issuance; and *Term Structure Slope* = difference between 12-months and one-month Libor rate at bond issuance. All specifications control for time and asset type fixed effects and for binary indicator variables for the different risk weight categories *RWC*. Standard errors are reported in parentheses and clustered by bank. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively.

	Model III Without bank FE		Model IV with bank FE	
Dependent Variable:	Coeff	AME	Coeff	AME
Standardized Investment Volume (%)	(1)	(2)	(3)	(4)
Spread	22.456***	0.510***	21.557***	0.654***
	(8.323)	(0.141)	(8.260)	(0.176)
Lag CAR	-350.479	-14.898*	241.822	-37.941**
	(549.487)	(7.880)	(1158.613)	(16.341)
Lag CAR × *Spread*	-119.856***		-130.757***	
	(46.794)		(41.437)	
Log Assets	-108.873***	0.924***	-168.642***	-0.468
	(30.407)	(0.221)	(49.687)	(2.664)
Log Assets × *Spread*	1.322		2.535*	
	(1.195)		(1.390)	
ABS Controls and Interactions:	Yes	Yes	Yes	Yes
Fixed Effects:				
RWC, Time, Asset Type	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes
N Observations	102,239	102,239	102,239	102,239
N Banks	58	58	58	58
N Bonds	1,884	1,884	1,884	1,884
Pseudo R^2	0.1374	0.1374	0.2239	0.2239

Table VII
Ratings Inflation and Risk Weight Bias

Reported are regression coefficients and average marginal effects (in %) of probit estimations. The dependent variable is 1 if the bank purchases the bond and zero otherwise. Models V and VI both explore the role of *Risk Weight Bias* in bond purchase decisions. *Risk Weight Bias* is a measure of risk weight misclassification and calculated as the ABS yield spread in excess of the average yield spread in the next lower *RWC* (see Appendix F). Only Model VI controls for bank fixed effects. Otherwise, the independent variables, fixed effects, and interactions are the same as in Table IV, columns (5) and (6): *Lag CAR* = capital adequacy ratio lagged by three months; and *Log Assets* = $Log(Bank\ Assets)$. The set of ABS controls contains the following variables: *Nominal Maturity* = nominal bond maturity; *WAL* = weighted average life; *Log Bond Size* = $Log(Bond\ Face\ Value)$; *Term Structure Level* = one-month Libor rate at bond issuance; and *Term Structure Slope* = difference between 12-months and one-month Libor rate at bond issuance. All specifications control for time and asset type fixed effects and for binary indicator variables for the different risk weight categories *RWC*. All specifications include a constant. Standard errors are reported in parentheses and clustered by bank. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively. The p-value of the Hosmer-Lemeshow goodness-of-fit test is reported for five groups (H0: probit correctly specified).

	Model V Without bank FE		Model VI with bank FE	
	Coeff	AME	Coeff	AME
Dep. Variable: *Purchase Yes/No*	(1)	(2)	(3)	(4)
Risk Weight Bias	0.573**	0.183***	0.611**	0.451***
	(0.232)	(0.061)	(0.242)	(0.098)
Lag CAR	−7.913	−0.251	5.422	−8.176
	(7.974)	(1.415)	(20.257)	(5.719)
Lag CAR × *Risk Weight Bias*	−2.906**		−3.376***	
	(1.306)		(1.283)	
Log Assets	−1.799***	0.266***	−3.179***	0.076
	(0.394)	(0.096)	(0.787)	(1.048)
Log Assets × *Risk Weight Bias*	0.044		0.074	
	(0.042)		(0.055)	
ABS Controls and Interactions:	Yes	Yes	Yes	Yes
Fixed Effects:				
RWC, Time, Asset Type	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes
N Observations	102,239	102,239	41,988	41,988
N Banks	58	58	23	23
N Bonds	1,884	1,884	1,884	1,884
Pseudo R^2	0.231	0.231	0.283	0.283
Hosmer-Lemeshow GoF (p-val.)	0.854	0.854	0.746	0.746

Table VIII
Ex Post Performance of ABS Positions

Reported are regression coefficients and average marginal effects (in %) of probit estimations. The dependent variable is 1 if the bank purchases the bond and zero otherwise. Models VII and VIII both explore the ex post performance of ABS bought by banks with different lagged CARs. The ex post performance of an ABS is measured by the 90days-delinquency rate nine months after ABS acquisition. Both probit models control for *Subordination* = part of deal subordinated to ABS standardized by collateral pool balance; *Dummy Guarantee* = 1 if ABS is guaranteed; *No. of Tranches* = number of tranches in ABS deal. Otherwise, the independent variables, fixed effects, and interactions are the same as in Table IV, columns (5) and (6): *Lag CAR* = capital adequacy ratio lagged by three months; and *Log Assets* = $Log(Bank\ Assets)$. The set of ABS controls contains the following variables: *Nominal Maturity* = nominal bond maturity; *WAL* = weighted average life; *Log Bond Size* = $Log(Bond\ Face\ Value)$; *Term Structure Level* = one-month Libor rate at bond issuance; and *Term Structure Slope* = difference between 12-months and one-month Libor rate at bond issuance. All specifications control for time and asset type fixed effects and for binary indicator variables for the different risk weight categories *RWC*. Only Model VIII controls for bank fixed effects. All specifications include a constant. Standard errors are reported in parentheses and clustered by bank. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively. The *p*-value of the Hosmer-Lemeshow goodness-of-fit test is reported for five groups (H0: probit correctly specified).

	Model VII Without bank FE		Model VIII with bank FE	
	Coeff	AME	Coeff	AME
Dep. Variable: *Purchase Yes/No*	(1)	(2)	(3)	(4)
Delinquency	0.041	−0.030***	0.181	−0.131**
	(0.044)	(0.011)	(0.112)	(0.056)
Lag CAR	19.404***	0.284	124.777***	−7.146
	(6.034)	(1.255)	(19.982)	(6.866)
Lag CAR × *Delinquency*	−0.823**		−2.434**	
	(0.358)		(1.049)	
Log Assets	−1.737***	0.207**	−7.385***	−1.066
	(0.538)	(0.083)	(1.239)	(0.854)
Log Assets × *Delinquency*	0.009		0.033	
	(0.017)		(0.030)	
ABS Controls and Interactions:	Yes	Yes	Yes	Yes
Fixed Effects:				
RWC, Time, Asset Type	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes
N Observations	72,452	72,452	22,969	22,969
N Banks	58	58	18	18
N Bonds	1,364	1,364	1,364	1,364
Pseudo R^2	0.300	0.300	0.382	0.382
Hosmer-Lemeshow GoF (p-val.)	0.641	0.641	0.005	0.005

Table IX
Robustness to Logit and Complementary Log-Log Specifications

Reported are regression coefficients and average marginal effects (in percent) of logit and complementary Log-Log estimations. The dependent variable is 1 if the bank purchases the bond and zero otherwise. The independent variables, fixed effects, and interactions are the same as in Table IV, columns (5) and (6) except that I do not control for bank fixed effects: *Spread* = yield spread of ABS (floating rate note); *Lag CAR* = capital adequacy ratio lagged by three months; and *Log Assets* = $Log(Bank\ Assets)$. The set of ABS controls contains the following variables: *Nominal Maturity* = nominal bond maturity; *WAL* = weighted average life; *Log Bond Size* = $Log(Bond\ Face\ Value)$; *Term Structure Level* = one-month Libor rate at bond issuance; and *Term Structure Slope* = difference between 12-months and one-month Libor rate at bond issuance. All specifications control for time and asset type fixed effects and for binary indicator variables for the different risk weight categories *RWC*. All specifications include a constant. Standard errors are reported in parentheses and clustered by bank. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively. The *p*-value of the Hosmer-Lemeshow goodness-of-fit test is reported for five groups (H0: probit correctly specified).

	Logit		Compl. Log-Log	
	Coeff	AME	Coeff	AME
Dep. Variable: *Purchase Yes/No*	(1)	(2)	(3)	(4)
Spread	1.062***	0.087**	1.056***	0.085*
	(0.355)	(0.043)	(0.349)	(0.044)
Lag CAR	−9.548	−0.139	−8.966	−0.123
	(21.507)	(1.453)	(21.181)	(1.455)
Lag CAR × *Spread*	−5.637***		−5.511***	
	(1.989)		(1.938)	
Log Assets	−4.442***	0.282***	−4.338***	0.283**
	(1.177)	(0.111)	(1.171)	(0.112)
Log Assets × *Spread*	0.037		0.028	
	(0.060)		(0.059)	
ABS Controls and Interactions:	Yes	Yes	Yes	Yes
Fixed Effects:				
RWC, Time, Asset Type	Yes	Yes	Yes	Yes
Bank	No	No	No	No
N Observations	102,239	102,239	102,239	102,239
N Banks	58	58	58	58
N Bonds	1,884	1,884	1,884	1,884
Pseudo R^2	0.229	0.229		
Hosmer-Lemeshow GoF (p-value)	0.540	0.540		

Appendix A. Stylized Portfolio Model

The following example illustrates the effect of regulation on the portfolio allocation when risk weights are coarse and, hence, not proportional to expected returns. I simplify the general model in (1) in two ways. First, I assume a single-factor model in which only systematic risk is compensated and in which the risk-free rate is set to zero. The return R_i of security i is normally distributed and given by

$$R_i = \beta_i R_S + \epsilon_i \quad \text{with} \quad \mathbb{E}(\epsilon_i) = \mathbb{E}(\epsilon_i R_S) = \mathbb{E}(\epsilon_i \epsilon_j) = 0 \tag{A1}$$

where R_S denotes the return of the systematic factor explaining ABS returns.[60] The expected return μ_i, variance σ_i^2, and covariance $\sigma_{i,j}$ follow as

$$\mu_i = \beta_i \mu_S \ , \quad \sigma_i^2 = \beta_i^2 \sigma_S^2 + \sigma_{\epsilon,i}^2 \ , \quad \sigma_{i,j} = \beta_i \beta_j \sigma_S^2 \ . \tag{A2}$$

Second, I assume that there are only three securities $i = 1, 2, 3$ with betas $0 < \beta_1 < \beta_2 < \beta_3$. Security 3 has a high risk weight w_h whereas securities 1 and 2 have a low risk weight w_l, which satisfies $0 < w_l < w_h$. Note that the non-discriminatory treatment of securities 1 and 2 by the regulator allows the bank to increase the expected portfolio return without incurring higher capital requirements. The bank can simply invest more of the capital allocated to the w_l-bucket into security 2 and less of it into security 1.

Proposition 1: Reaching for Yield and Regulatory Arbitrage

The bank increases investment x_2 relative to x_1 if the regulatory constraint is binding ($\kappa = \mathbf{w}'\mathbf{x}$).

Proof: It suffices to check whether the derivative $\partial \left(\frac{x_2}{x_1 + x_2} \right) / \partial \lambda$ is positive. This

[60] As returns are normally distributed, the optimal solution in (2) maximizes the expected utility of an investor with utility function $U(W) = -exp\{-\gamma W\}$. Constant absolute risk aversion γ ensures that higher bank equity affects the relative mix of securities in the portfolio only through a higher κ in the regulatory constraint but not through the bank's preferences. In section 6.3 I will test whether the possibly larger risk appetite of weakly capitalized banks alone can explain risk weight arbitrage.

is indeed true for $\mu_S > 0$:

$$\frac{\partial\left(\frac{x_2}{x_1+x_2}\right)}{\partial\lambda} = \frac{(\beta_2-\beta_1)\sigma^2_{\epsilon,3}\mu_S w_{low}}{Denom.} \cdot \left[\left(\beta_1^2\sigma^2_{\epsilon,2}\sigma^2_{\epsilon,3} + \beta_2^2\sigma^2_{\epsilon,1}\sigma^2_{\epsilon,3} + \beta_3^2\sigma^2_{\epsilon,1}\sigma^2_{\epsilon,2}\right)\sigma_S^2 + \sigma^2_{\epsilon,1}\sigma^2_{\epsilon,2}\sigma^2_{\epsilon,3}\right] \tag{A3}$$

where the denominator is given as

$$Denom. = \left\{-\left(\beta_2\sigma^2_{\epsilon,1}+\beta_1\sigma^2_{\epsilon,2}\right)\sigma^2_{\epsilon,3}\cdot\mu_S \;+\; \lambda\cdot\left[\left(\sigma^2_{\epsilon,1}+\sigma^2_{\epsilon,2}\right)\sigma^2_{\epsilon,3}\cdot w_{low} + \; w_{high}\sigma_S^2 \cdot \left(-\beta_3\left(\beta_2\sigma^2_{\epsilon,1}+\beta_1\sigma^2_{\epsilon,2}\right) + w_{low}\left(\beta_3^2\left(\sigma^2_{\epsilon,1}+\sigma^2_{\epsilon,2}\right)+(\beta_1-\beta_2)^2\sigma^2_{\epsilon,3}\right)\right)\right]\right\}^2. \tag{A4}$$

The bank reaches for yield in the low risk weight category w_{low} if the regulatory constraint is binding ($\lambda > 0$).

A binding regulatory constraint limits the total size of the portfolio and, in particular, the position x_3 in security 3 with the highest risk weight w_h and the highest expected return. To partly compensate for the reduced portfolio return, the bank invests less of the capital allocated to the w_l-bucket into security 1 and more of it into security 2.

Although the bank can exploit the coarseness of the w_l-bucket, which treats securities 1 and 2 the same, regulation still achieves some reduction of portfolio risk. For sufficiently large w_h, the portfolio beta β_{PF} is strictly lower if the regulatory constraint is binding $\left(\frac{\partial\beta_{PF}}{\partial\lambda} < 0\right)$.[61] However, regulation can only curtail risk taking as long as securities are correctly classified into risk weight categories and risk weights are non-decreasing in systematic risk. To illustrate how the misclassification of securities can make regulation ineffective, I now assume that security 2 with the low risk weight w_l and not security 3 has the highest beta ($0 < \beta_1 < \beta_3 < \beta_2$).

Proposition 2: Misclassification of ABS and Portfolio Risk

For $\beta_2 >> \beta_3$, the portfolio beta β_{PF} is higher if the regulatory constraint is binding and $\kappa = \mathbf{w}'\mathbf{x}$.

[61] See Proof to Proposition 2.

Proof: The portfolio beta is defined as

$$\beta_{PF} = \frac{x_1\beta_1 + x_2\beta_2 + x_3\beta_3}{x_1 + x_2 + x_3} \ . \tag{A5}$$

Its derivative with respect to λ is

$$\begin{aligned} \frac{\partial \beta_{PF}}{\partial \lambda} = \underbrace{\frac{\mu_S \cdot \left[\left(\beta_1^2\sigma_{\epsilon,2}^2\sigma_{\epsilon,3}^2 + \beta_2^2\sigma_{\epsilon,1}^2\sigma_{\epsilon,3}^2 + \beta_3\sigma_{\epsilon,1}^2\sigma_{\epsilon,2}^2\right)\sigma_S^2 + \sigma_{\epsilon,1}^2\sigma_{\epsilon,2}^2\sigma_{\epsilon,3}^2\right]}{Denominator}}_{>0} \\ \cdot \underbrace{\begin{aligned} &\left[\left(\beta_3(\beta_3-\beta_2)\sigma_{\epsilon,1}^2 + \beta_3(\beta_3-\beta_1)\sigma_{\epsilon,2}^2 + (\beta_1-\beta_2)^2\sigma_{\epsilon,2}^2\right)\cdot w_{low} \right. \\ &\qquad \left. - \left(\beta_2(\beta_3-\beta_2)\sigma_{\epsilon,1}^2 + \beta_1(\beta_3-\beta_1)\sigma_{\epsilon,2}^2\right)\cdot w_{high}\right] \end{aligned}}_{\gtreqless 0} \end{aligned} \tag{A6}$$

where the positive denominator is omitted for brevity. It follows that $\frac{\partial \beta_{PF}}{\partial \lambda}$ is negative whenever

$$w_{high} > \frac{\beta_3(\beta_3-\beta_2)\sigma_{\epsilon,1}^2 + \beta_3(\beta_3-\beta_1)\sigma_{\epsilon,2}^2 + (\beta_1-\beta_2)^2\sigma_{\epsilon,2}^2}{\beta_2(\beta_3-\beta_2)\sigma_{\epsilon,1}^2 + \beta_1(\beta_3-\beta_1)\sigma_{\epsilon,2}^2} \cdot w_{low} \ . \tag{A7}$$

Note that the right hand side of Inequality (A7) is strictly larger than w_{low} for $0 < \beta_1 < \beta_2 < \beta_3$. Hence, for sufficiently large w_{high}, the bank will choose a lower portfolio-beta if its regulatory constraint is binding.

This result changes when securities are misclassified. In Proposition 2, I assume that security 2 has the highest beta so that $0 < \beta_1 < \beta_3 < \beta_2$. Provided that the difference in systematic risk between securities 2 and 3 is sufficiently large so that

$$\beta_3 < \frac{\beta_2^2\sigma_{\epsilon,1}^2 + \beta_1^2\sigma_{\epsilon,2}^2}{\beta_2\sigma_{\epsilon,1}^2 + \beta_1\sigma_{\epsilon,2}^2} < \beta_2 \ , \tag{A8}$$

then a bank with a binding regulatory constraint chooses a higher portfolio-beta than an unconstrained bank. To see this, note that (A8) implies that $\beta_2(\beta_3 - \beta_2)\sigma_{\epsilon,1}^2 + \beta_1(\beta_3-\beta_1)\sigma_{\epsilon,2}^2$ in (A6) is negative. It follow that derivative $\frac{\partial \beta_{PF}}{\partial \lambda}$ is now positive if Inequality (A7) is satisfied. At the same time, (A8) also implies that the right hand side of Inequality (A7) is now smaller than w_{low}. As w_{high} must be larger than w_{low}, it follows that Inequality (A7) is always satisfied and that $\frac{\partial \beta_{PF}}{\partial \lambda}$ is, hence, always positive provided Inequality (A8) is true. If the regulatory constraint is binding and misclassification of securities 2 and 3 is as pronounced as in Inequality (A8), the bank chooses a *higher* portfolio-beta.

Similarly, it can be shown that total investment in all three securities together is higher if the regulatory constraint is binding and securities are misclassified ($\beta_2 >> \beta_3$). To see this, it suffices to compute $\frac{\partial(x_1+x_2+x_3)}{\partial \lambda}$ which is positive if (A8) is satisfied. To sum up, whenever (A8) is satisfied and security 2 has a much higher beta than security 3, a bank with a binding regulatory constraint will build a *larger* ABS portfolio with a *higher* portfolio-beta.

When the regulatory constraint is binding, the bank increases the portfolio share of security 2 whose beta is highest and whose risk weight is unjustifiably low. As long as security 2 exhibits sufficiently higher systematic risk than security 3 ($\beta_2 >> \beta_3$ and $w_2 < w_3$), a bank with a binding regulatory constraint will have a higher portfolio beta.

Propositions 1 and 2 are formulated for banks with *binding* regulatory constraints. Yet, the predictions are made for banks with *tight* regulatory constraints.[62] Broadening the analysis to banks with tight but unbinding constraints is necessary because, in reality, banks rarely operate with binding regulatory constraints and "want to hold a buffer of capital so that they will still meet regulatory requirements following an earnings shock (Boyson et al., 2016)."

Appendix B. Identifying Risk Weight Categories

I determine the appropriate risk weight category *RWC* of a bond using Table I, column (3), and introduce dummies for rating buckets with the same IRB-RBA base risk weights. Choosing the IRB-RBA base risk weights for all bonds and all banks has two disadvantages. First, I implicitly assume that all banks use the IRB approach and not the SA, although the data do not allow me to verify this assumption. However, as I only consider large sophisticated institutions with assets worth more than €10bn and discard local cooperative

[62] In a dynamic model I could also analyze regulatory arbitrage by banks with tight but unbinding regulatory constraints. However, writing a dynamic model goes beyond the scope of this section.

and savings banks, this assumption is likely to be satisfied for most banks in the sample. Furthermore, as risk weight categories are coarser under the SA than under the IRB-RBA, I can only *underestimate* regulatory arbitrage by banks that use the SA. To see this, consider a bank that uses the SA and chooses between AAA and AA rated ABS in the 20% risk weight category of the SA (Table I, column 1). If the bank seeks high yields, it will acquire more AA than AAA rated bonds without incurring higher capital requirements under the SA. But because I control for the IRB-RBA base risk weights, which are different for AAA and AA rated securities, I cannot identify such risk-shifting from AAA to AA rated securities. I only identify reaching for yield within the AAA and within the AA category.

The second disadvantage of applying the IRB-RBA base risk weights to all ABS is that some securities might be senior or backed by non-granular collateral pools and hence deserve risk weights from Table I, columns (2) or (4). The data offers no clear-cut way to identify these securities. However, the large majority of senior tranches in structured debt deals carry a AAA rating, which I control for with a binary dummy variable. In some specifications I control for the combined face value of subordinated deal tranches that are junior to a given ABS. To the extent that larger collateral pools tend to be less granular, I proxy collateral granularity by the control variable *Log Bond Size*.[63]

Appendix C. Statistical Significance of Interaction Effects

Graphs (1) and (2) in Figure 6 illustrate the interaction effects *Spread* × *Lag CAR* and *Spread* × *Log Assets*. In Table C.1 I show that the average marginal effect of *Spread* is significantly larger at low CARs and at high values of *Log Assets*. Table C.1, columns (2) and (5) report the average marginal effect (in percent) of the bond yield spread on the probability that the bank purchases the bond for different values of *Lag CAR* and *Log Assets*. In column (3), I report the p-values for testing whether the average marginal effect of *Spread* is significantly *smaller* at capital adequacy ratios of 0.09, 0.15 and 0.20 than at *Lag CAR* = 0.08. The null hypothesis is $AME(Lag\ CAR = 0.09/0.15/0.20) \geq AME(Lag$

[63]The additional distinction between securitization and resecuritization exposures under Basel II.5 concerns only the 2.6% of the ABS in the sample that were issued after the compliance date for Basel II.5. I control for resecuritization with a dummy variable, which is 1 for CDOs/CLOs.

Table C.1
Interaction Effects between Yield Spread, Capital Adequacy Ratio and Bank Size

Reported are the interaction effects *Spread* × *Lag CAR* and *Spread* × *Log Assets* in Models I and II of Table V. Columns (2) and (5) report the average marginal effect (in percent) of a one percent change of the bond yield spread on the probability that the bank purchases the bond. The average marginal effect is reported for different values of *Lag CAR* and *Log Assets*. Standard errors of average marginal effects are reported in parentheses. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively. In column 3, I test whether the average marginal effect of *Spread* is significantly smaller at capital adequacy ratios of 0.09, 0.15 and 0.20 than at $Lag\ CAR = 0.08$. The null hypothesis is $AME(Lag\ CAR = 0.09/0.15/0.20) \geq AME(Lag\ CAR = 0.08)$. To compute the one-sided p-values reported in column (3), I first compute the test statistic for an equality test, which is chi-squared distributed with one degree of freedom. It equals the square of the standard normal for which one-sided p-values can be computed. Column (6) shows the one-sided p-values for the test whether the average marginal effect of *Spread* is significantly smaller at $Log\ Assets = 0.2$, 1.6 and 2.8 than at $Log\ Assets = 3.0$.

Panel A: Interaction Effects in Model I

Spread × *Lag CAR*			*Spread* × *Log Assets*		
Lag CAR (%) (1)	AME (*Spread*) (%) (2)	One-sided test (3)	*Log Assets* (4)	AME (*Spread*) (%) (5)	One-sided test (6)
8	0.229***	-	0.2	0.015	0.020
	(0.083)			(0.012)	
9	0.190***	0.042	1.6	0.049*	0.026
	(0.063)			(0.026)	
15	0.079***	0.028	2.8	0.183**	0.040
	(0.029)			(0.080)	
20	0.017	0.019	3.0	0.227**	-
	(0.041)			(0.102)	

Panel B: Interaction Effects in Model II

Spread × *Lag CAR*			*Spread* × *Log Assets*		
Lag CAR (%) (1)	AME (*Spread*) (%) (2)	One-sided test (3)	*Log Assets* (4)	AME (*Spread*) (%) (5)	One-sided test (6)
8	1.279***	-	0.2	0.088	0.386
	(0.464)			(0.350)	
9	0.902***	0.008	1.6	0.168	0.420
	(0.315)			(0.182)	
15	0.183***	0.007	2.8	0.239	0.428
	(0.049)			(0.187)	
20	0.021	0.004	3.0	0.254	-
	(0.057)			(0.266)	

$CAR = 0.08$). Column (6) shows one-sided p-values for a similar test for bank size.

Appendix D. Robustness of Investment Volume Regressions

In Table D.1, columns (1) and (2), I estimate ordinary least squares regressions without and with bank fixed effects to explain the (standardized) investment volume of ABS acquisitions. I include dummies for risk weight categories *RWC* as well as the interactions *RWC* × *Lag CAR* and *RWC* × *Log Assets*. Conditional on *RWC*, a higher yield spread increases the fraction of capital that a bank invests into an ABS. The negative interaction effect *Spread* × *Lag CAR* is significant at the 10% level suggesting that banks with low capital adequacy ratios engage more in risk weight arbitrage.

In a second robustness check, I compute the logarithmic transform of the investment volume, which reduces the skewness of the dependent variable from 2.20 to -0.79 and its kurtosis from 6.95 to 4.46 in the sample of positive values. I rerun the OLS and Tobit regressions with the *Log Standardized Investment Volume* (Table D.1, columns (3) to (8)). The interaction effects *RWC* × *Lag CAR* and *RWC* × *Log Assets* become significant at the 5% level in the OLS regressions. The interaction effect *Spread* × *Lag CAR* estimated in the Tobit regressions is illustrated in Figure D.1, Graph (1) without and Graph (2) with bank fixed effects.

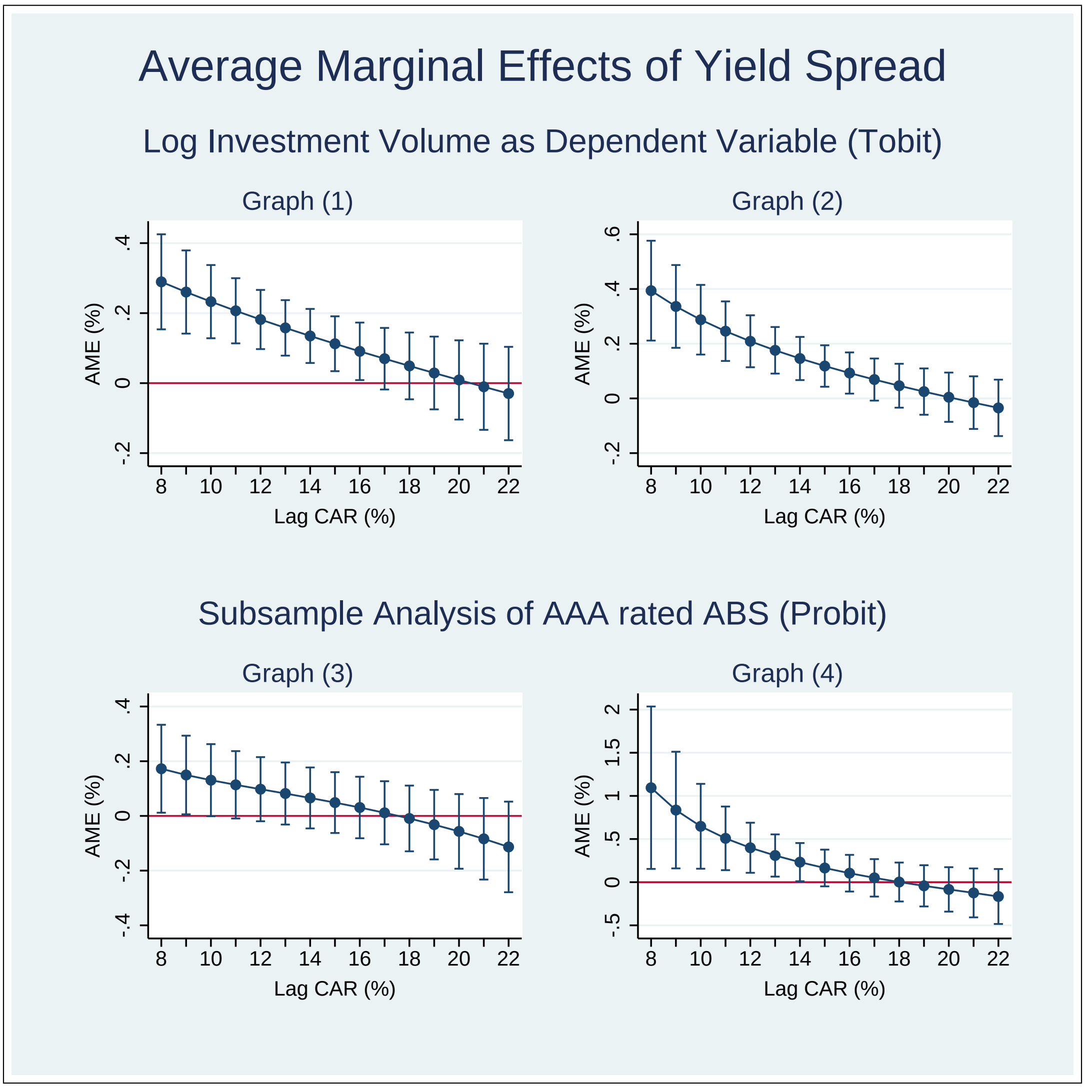

Figure D.1. Alternative specifications for explaining investment volumes. Graphs (1) and (2) show the average marginal effect of the bond yield spread on the *Log Standardized Investment Volume* that a bank with given *Lag CAR* invests into the ABS in specifications without and with bank fixed effects. Graphs (3) and (4) show the average marginal effect of the bond yield spread on the probability that a bank with given *Lag CAR* buys a bond in the subsample of *AAA* rated ABS. Graphs (1) and (2) are estimated with Tobit models, Graphs (3) and (4) with probit models. Only Graphs (2) and (4) control for bank fixed effects. Confidence intervals are drawn for the 5% level.

Table D.1
Alternative Specifications for Explaining Investment Volumes

The dependent variable is the standardized investment volume defined as the Euro-amount invested into ABS *s* by bank *b* as a percentage of the aggregated Euro-amount that bank *b* invests in all ABS purchased in the same year-quarter. In columns (3) to (8) I use the logarithmic transform of the standardized investment volume as dependent variable. Columns (1) to (4) report the coefficients (marginal effects) of OLS regressions. Columns (5) to (8) report the regression coefficients and the marginal effects of Tobit specifications. Marginal effects in Tobit regressions are computed for the left-truncated log investment volume. Bank fixed effects are included in columns (2), (4), (7), and (8). Otherwise, the independent variables, fixed effects, and interactions are the same as in Table IV, columns (5) and (6): *Spread* = yield spread of ABS (floating rate note); *Lag CAR* = capital adequacy ratio lagged by three months; and *Log Assets* = *Log*(*Bank Assets*). The set of ABS controls contains the following variables: *Nominal Maturity* = nominal bond maturity; *WAL* = weighted average life; *Log Bond Size* = *Log*(*Bond Face Value*); *Term Structure Level* = one-month Libor rate at bond issuance; and *Term Structure Slope* = difference between 12-months and one-month Libor rate at bond issuance. All specifications control for time and asset type fixed effects and for binary indicator variables for the different risk weight categories *RWC*. All specifications include a constant. Standard errors are reported in parentheses. They are clustered by bank and ABS deal in the OLS regressions. In the Tobit regressions they are only clustered by bank. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively.

	OLS		OLS		Tobit		Tobit	
Dep. variable:	Std. Inv. Vol.		Log(Std. Inv. Vol.)		Log(Std. Inv. Vol.)		Log(Std. Inv. Vol.)	
	ME	ME	ME	ME	Coeff	AME	Coeff	AME
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Spread	0.032**	0.031**	0.004	0.004	7.245***	0.144***	6.778***	0.172***
	(0.016)	(0.015)	(0.003)	(0.003)	(2.612)	(0.040)	(2.395)	(0.044)
Lag CAR	0.216	0.186	-0.023	-0.049	-95.083	-3.994**	135.253	-9.586***
	(0.931)	(0.873)	(0.287)	(0.310)	(158.456)	(1.902)	(340.218)	(3.693)
Lag CAR × *Spread*	−0.142*	−0.135*	-0.034**	-0.030**	-39.351***		-43.334***	
	(0.073)	(0.072)	(0.016)	(0.015)	(14.967)		(12.718)	
Log Assets	−0.139*	−0.183	-0.102***	-0.127***	-34.834***	0.248***	-53.188***	-0.157
	(0.079)	(0.115)	(0.034)	(0.040)	(7.315)	(0.058)	(12.406)	(0.663)
Log Assets × *Spread*	0.006	0.006	0.005**	0.005**	0.469		0.901**	
	(0.004)	(0.004)	(0.002)	(0.002)	(0.381)		(0.420)	
ABS Controls and Interactions:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects:								
RWC, Time, Asset Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank	No	Yes	No	Yes	No	No	Yes	Yes
N Obs	102239	102239	102239	102239	102239	102239	41988	41988
N Banks	58	58	58	58	58	58	23	23
N Bonds	1,884	1,884	1,884	1,884	1,884	1,884	1,884	1,884
Pseudo R^2	0.0028	0.0054	0.0102	0.0176	0.1606	0.1606	0.1878	0.1878
Double-clustered s.e.	Yes	Yes	Yes	Yes	No	No	No	No

Appendix E. Yield Spread and Capital Requirement of Average ABS Position

I estimate the yield spread and capital requirement of the average ABS bought by banks with lagged capital adequacy ratios (CARs) of 8%, 9%, 10%, ..., 22%. In a first step, I use the estimated regression coefficients $\hat{\beta}$ of Model I (Table V, column 1) to predict the probability that a bank with given *Lag CAR* buys an ABS with a given yield spread. The prediction $\widehat{AP_i}$ of observation i adjusted for a given bond yield spread y and lagged CAR c is given as

$$\widehat{AP_i}(c, y) = \Pr(\hat{\beta}\mathbf{X}_i | c, y) \tag{E1}$$

where the variable vector $\mathbf{X}$ takes the values of observation i except for *Lag CAR* and *Spread* which are fixed at c and y (Williams, 2012). The adjusted prediction $\widehat{AP_i}$ is computed for each of the N observations in the sample. In a second step, I compute the *average* adjusted prediction $\widehat{AAP}$ defined as

$$\widehat{AAP}(c, y) = N^{-1} \sum_i \Pr(\hat{\beta}\mathbf{X}_i | c, y) \ . \tag{E2}$$

Average adjusted predictions are computed for a set $\mathbf{Y}$ of representative yield spreads chosen as the 10%, 20%, 30%, ..., 90% quantiles of the yield spread distribution. Appendix Table E.1, Panel A shows the predicted probabilities for a bank with a lagged CAR of 9%. For example, an ABS with a yield spread of 16bps (10% quantile of the yield spread distribution) is bought with a predicted probability of 0.225%. I use the average adjusted predictions $\widehat{AAP}$ to compute portfolio weights

$$\omega(c, y) = \frac{\widehat{AAP}(c, y)}{\sum_{i \in \mathbf{Y}} \widehat{AAP}(c, i)} \ , \tag{E3}$$

$$\text{for } \mathbf{Y} = \{16bps, 30bps, 35bps, 50bps, 60bps, 85bps, 115bps, 150bps, 220bps\}. \tag{E4}$$

which are shown for a *Lag CAR* equal to 9% in Table E.1, Panel A. For example, an ABS with a yield spread of 16bps has a portfolio weight $\omega(c = 9\%, y = 16bps)$ of 0.067 in the portfolio of a bank with a CAR of 9%. In a last step I use the weights $\omega(c, y)$ of the representative yield spreads $y \in \mathbf{Y}$ to compute the predicted yield spread of the average ABS purchased

Table E.1
Predicted ABS Yield Spreads and Risk Weights

The table shows the predicted probabilities (in percent) that banks with *Lag CARs* equal to 9%, 15%, or 20% buy an ABS with a given yield spread or risk weight. The predicted probabilities are estimated with the regression coefficients of Table III, Model I, and are adjusted for different values of *Lag CAR* (lagged capital adequacy ratio), *Spread* (bond yield spread), and IRB base risk weight categories. Standard errors are reported in parentheses. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively. The predicted purchase probabilities are then used to compute the weights of the ABS with different spreads/risk weights in the portfolio of a bank with given *Lag CAR*.

Panel A: Capital Adequacy Ratio = 9%									
Yield Spread	16bps	30bps	35bps	50bps	60bps	85bps	115bps	150bps	220bps
Predicted prob.	0.225***	0.246***	0.254***	0.280***	0.298***	0.348***	0.419***	0.516***	0.771***
	(0.069)	(0.075)	(0.077)	(0.083)	(0.088)	(0.103)	(0.124)	(0.157)	(0.253)
Weights	0.067	0.073	0.076	0.083	0.089	0.104	0.125	0.154	0.230
IRB Base RWC	12%	15%	18%	20%	35%	75%	100%	425%	
Predicted prob.	0.415***	0.403*	0.539	0.443**	0.119	0.052**	0.040	0.048	
	(0.142)	(0.228)	(0.534)	(0.210)	(0.112)	(0.023)	(0.029)	(0.031)	
Weights	0.201	0.195	0.262	0.215	0.058	0.025	0.021	0.023	
Panel B: Capital Adequacy Ratio = 15%									
Yield Spread	16bps	30bps	35bps	50bps	60bps	85bps	115bps	150bps	220bps
Predicted prob.	0.219***	0.229***	0.233***	0.244***	0.252***	0.273***	0.300***	0.334***	0.414***
	(0.053)	(0.055)	(0.056)	(0.058)	(0.060)	(0.064)	(0.072)	(0.082)	(0.111)
Weights	0.088	0.092	0.093	0.098	0.101	0.109	0.120	0.134	0.166
IRB Base RWC	12%	15%	18%	20%	35%	75%	100%	425%	
Predicted prob.	0.343***	0.177***	0.003	0.104**	0.040	0.066***	0.070	0.067	
	(0.089)	(0.057)	(0.003)	(0.042)	(0.040)	(0.024)	(0.053)	(0.046)	
Weights	0.394	0.204	0.003	0.120	0.046	0.076	0.080	0.077	
Panel C: Capital Adequacy Ratio = 20%									
Yield Spread	16bps	30bps	35bps	50bps	60bps	85bps	115bps	150bps	220bps
Predicted prob.	0.272***	0.275***	0.276***	0.278***	0.280***	0.284***	0.289***	0.296***	0.309**
	(0.094)	(0.094)	(0.093)	(0.093)	(0.093)	(0.094)	(0.097)	(0.102)	(0.120)
Weights	0.106	0.107	0.108	0.109	0.109	0.111	0.113	0.116	0.121
IRB Base RWC	12%	15%	18%	20%	35%	75%	100%	425%	
Predicted prob.	0.364***	0.110	0.000	0.037	0.022	0.109**	0.147	0.120	
	(0.122)	(0.070)	(0.000)	(0.030)	(0.023)	(0.043)	(0.121)	(0.085)	
Weights	0.401	0.121	0.000	0.040	0.024	0.120	0.162	0.132	

by a bank with *Lag CAR* equal to c:

$$\widehat{YS}(c) = \sum_{y \in \mathbf{Y}} \omega(c, y) \cdot y. \tag{E5}$$

Next, I calculate the risk weight of the average ABS bought by banks with different CARs. I compute average adjusted predictions $\widehat{AAP}(c, r)$ for the probability that a bank with a *Lag CAR* of c buys an ABS in risk weight category r. For example, an ABS with an IRB base risk weight of 12% (AAA rated) is bought with a predicted probability of 0.415% by a bank with a *Lag CAR* equal to 9% (see Appendix Table E.1, Panel A).[64] Then I weight the different risk weight categories (12%, 15%, 18%, etc.) with the predicted purchase probabilities so that the average risk weight is calculated as

$$\widehat{RWC}(c) = \sum_{r \in RWC} \omega(c, r) \cdot r. \tag{E6}$$

Finally, the average capital requirement per Euro invested is computed as 8% of $\widehat{RWC}(c)$.

Appendix F. Calculation of Risk Weight Classification Bias

I call an ABS misclassified if the market requires a risk premium too high to be consistent with the assigned risk weight. In a first step, I regress the yield spread YS on a set of rating dummies for the different IRB base risk weights (RWC_{AAA}, $RWC_{AA+,AA,AA\text{-}}$, RWC_{A+}, ...) and a set of bond controls BC.[65]

$$YS = \beta_{RWC}\ RWC + \beta_{BC}\ BC + \varepsilon \tag{F1}$$

Then the YS of each ABS is corrected for the spread component that is explained by the bond controls ($YS - \widehat{\beta}_{BC} BC$). Finally, the *Risk Weight Bias* of a security in risk weight

[64] The IRB base risk weight categories for ABS with credit ratings *BBB+*, *BB+*, *BB-* and *Below BB- or Unrated* are missing in the regression sample and, therefore, in Table E.1.

[65] The bond controls are issuance year dummies, *Term Structure Level, Term Structure Slope*, *Nominal Maturity* and *Weighted Avg. Life* at bond issuance, *Log Bond Size* and asset type dummies.

category r is defined as the (corrected) yield spread in excess of the average spread implied by the next lower risk weight category $(r+1)$.[66]

$$Risk\ Weight\ Bias = \max\{\widehat{YS}^{corrected} - \widehat{\beta}_{RWC}(r+1), 0\} \tag{F2}$$

The cut-off $\widehat{\beta}_{RWC}(r+1)$ in Eq. (F2) is conservative in the sense that it ignores *Risk Weight Bias* of securities with yield spreads below the average spread implied by the next lower risk weight category $(r+1)$. Note that *Risk Weight Bias* is defined as a directed error which is positive only for securities whose ratings are too optimistic. By contrast, overly pessimistic ratings, which are arguably less harmful from the financial stability perspective, are ignored.

Appendix G. Delinquency Data

I use a sample of 1,529 ABS for which Moody's database "Performance Data Services" has information on the 90days-delinquency rate measured in collateral pools nine months after bond issuance. If no observation for the delinquency rate exists nine months after deal closure, the closest observation between six and 12 months after deal closure is chosen and linearly adjusted as in Efing & Hau (2015). To reduce the influence of outliers and data errors, the delinquency rate is winsorized at the 1% level in each tail. The average 90days-delinquency rate is 0.95% and has a standard deviation of 2.10%.

The sample of bonds with delinquency data is not a sub-sample of the bonds used in Section IV.A. Instead, this sample also comprises ABS for which I do not have data on yield spreads, that are not issued at par or are not denoted in Euro. Fourty-two percent of the sample with delinquency data are residential mortgage-backed securities, the rest are other asset-backed securities. Forty-three percent of this sample is backed by collateral from the USA, 21% by Spanish, 12% by British, 9% by Dutch, and 4% by German collateral.

Moody's database also contains information about levels of credit enhancement. The average subordination level of a security, defined as the value of subordinated deal tranches standardized by the collateral pool balance, is 10% and has a standard deviation of 10%. The subordination level is winsorized at the 1% level in each tail of its distribution. Five

[66] *Risk Weight Bias* is winsorized at the 1% level in each tail. It has a sample average of 18bps and a standard deviation of 48bps (Table II, Panel C).

percent of the ABS benefit from some kind of guarantee. The average ABS belongs to a deal with five other tranches.

Appendix H. Risk Weight Bias and Collateral Delinquency in OLS Regressions

I report coefficient estimates from OLS regressions for the probability that a bank buys a given ABS in Table H.1 (reported in %). Column (2) uses the binary variable *Dummy: 1 if Lag CAR* $<$ *Q50* which equals one if *Lag CAR* is smaller than the median. Otherwise, the control variables, fixed effects, and interactions are the same as in column (3) of Table VII and in column (3) of Table VIII, respectively.

Table H.1
Risk Weight Bias and Collateral Delinquency in OLS Regressions

I use OLS regressions to estimate the marginal effects of various bank and ABS characteristics on the probability that a bank buys a given ABS (reported in %). The dependent variable is 1 if the bank purchases the bond and zero otherwise. The independent variables are: *Risk Weight Bias* = measure of risk weight misclassification; *Delinquency* = bond collateral delinquency; *Lag CAR* = capital adequacy ratio lagged by three months; *Lag CAR* < *Q50* = 1 if *Lag CAR* below median and 0 otherwise; and *Log Assets* = *Log*(*Bank Assets*). The set of ABS controls contains the following variables: *Nominal Maturity* = nominal bond maturity; *WAL* = weighted average life; *Log Bond Size* = *Log*(*Bond Face Value*); *Term Structure Level* = one-month Libor rate at bond issuance; and *Term Structure Slope* = difference between 12-months and one-month Libor rate at bond issuance. Both specifications control for asset type, time, and bank fixed effects and for binary indicator variables for the different risk weight categories *RWC*. The specification in column (2) also controls for *Subordination* = part of deal subordinated to ABS standardized by collateral pool balance, *Dummy Guarantee* = 1 if ABS is guaranteed; and *No. of Tranches* = number of tranches in ABS deal. Both specifications include a constant and interactions of their respective ABS controls, RWC, asset type, and time dummies with *Lag CAR* and *Log Assets*. Robust standard errors are reported in parentheses and clustered by bank and by ABS-deal. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively.

Dep. Variable: *Purchase Yes/No*	(1)	(2)
Risk Weight Bias	0.017	
	(-0.072)	
Delinquency		-0.004
		(-0.014)
Lag CAR	-1.150	
	(-4.896)	
Lag CAR × *Risk Weight Bias*	-0.619*	
	(-0.339)	
Dummy: 1 if Lag CAR < *Q50*		-0.415
		(-0.292)
(Lag CAR < *Q50)* × *Delinquency*		0.039**
		(-0.017)
Log Assets	-1.881***	-1.526***
	(-0.629)	(-0.098)
Log Assets × *Risk Weight Bias*	0.172**	
	(-0.075)	
Log Assets × *Delinquency*		-0.042***
		(-0.013)
ABS Controls and Interactions:	Yes	Yes
Fixed Effects:		
RWC, Time, Asset Type	Yes	Yes
Bank	Yes	Yes
N Observations	102,239	72,452
N Banks	58	58
N Bonds	1,884	1,364
R^2	0.021	0.022
Double-clustered s.e.	Yes	Yes

Imprint and Acknowledgements

Note
This paper is the joint winner of the ESRB's Ieke van den Burg research prize, 2016. This annual prize recognises outstanding research conducted by young scholars on a topic related to the ESRB's mission.

The paper was selected by a committee of the Advisory Scientific Committee comprising Prasanna Gai, Ross Levine, Marco Pagano, Richard Portes and David Thesmar. The committee considered the paper to be a very clean and methodical empirical study of an essential issue, namely regulatory arbitrage. The paper is also in keeping with the spirit of the ESRB's research prize, which is administered in the spirit of a notion held dear by Ms van den Burg: namely that "finance should serve society".

Acknowledgements
I am grateful to seminar participants at the Deutsche Bundesbank, the European Central Bank, and the New York FED for sharing their expertise. Helpful comments were received after presentations at the Banque de France-Toulouse School of Economics conference on "Securitisation: the way forward?", the 14th International Conference on Credit Risk Evaluation (Venice), the annual meeting of the European Economic Association (2015), and the SFI Research Days in Gerzensee (2015). Special thanks go to an anonymous referee at the Deutsche Bundesbank, Bruno Biais, Claire Célérier, Sergey Chernenko, Jean Edouard Colliard, Darrell Due, Andrew Ellul, Rüdiger Fahlenbrach, Harald Hau, René Hegglin, Florian Heider, Thomas Kick, Alexander Michaelides, Steven Ongena, Natacha Parée, Jean-Charles Rochet, João A. C. Santos, Stephen Schaefer, David Smith, René M. Stulz, David Thesmar, Gregory F. Udell, James Vickery, and to the Bundesbank for providing the data. I am also grateful to seminar participants at Copenhagen Business School, Frankfurt School of Finance & Management, HEC Montréal, HEC Paris, Indiana University (Kelley), INSEAD, Imperial College, Laval University, Ohio State University, Tilburg University, Toulouse School of Economics, the Universities of Brussels, Geneva, Notre Dame, Rochester, Virginia (McIntire), and Zürich, and at Vienna University of Economics and Business.

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ISSN	2467-0677 (online)
ISBN	978-92-95081-52-9 (online)
DOI	10.2849/658224 (online)
EU catalogue No	DT-AD-16-022-EN-N (online)