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Arbitraging the Basel securitization framework: evidence from German ABS investment

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Non-technical summary

Research Question

The 2007-2009 financial crisis has raised fundamental questions about the effectiveness of the Basel II Securitization Framework, which regulates bank investments into asset-backed securities (ABS). The Basel Committee on Banking Supervision (2014) has identified "mechanic reliance on external ratings" and "insufficient risk sensitivity" as two major weaknesses of the framework. Yet, the full extent to which banks actually exploit these shortcomings and evade regulatory capital requirements is not known. This paper analyzes the scope of risk weight arbitrage under the Basel II Securitization Framework.

Contribution

A lack of data on the individual asset holdings of institutional investors has so far prevented the analysis of the demand-side of the ABS market. I overcome this obstacle using the Securities Holdings Statistics of the Deutsche Bundesbank, which records the on-balance sheet holdings of banks in Germany *on a security-by-security basis*. I analyze investments in ABS with an external credit rating to uncover risk weight arbitrage on the *demand-side* of the ABS market.

Results

The analysis delivers three main results. First, I provide security-level evidence that banks arbitrage Basel II risk weights for ABS. Banks tend to buy the securities with the highest yields and the worst collateral in a group of ABS with the same risk weight (and, therefore, the same capital charge). My findings corroborate the hypothesis that institutional investors bought risky ABS to some extent for motives of regulatory arbitrage.

Second, banks operating with low capital adequacy ratios close to the regulatory minimum requirement are found to arbitrage risk weights most aggressively. From a financial stability perspective this finding is troubling as it implies that the presumably more fragile banks are also most pervasively optimizing the very capital regulation designed to constrain them.

Third, banks with tight regulatory constraints buy *riskier* ABS with *lower* capital requirements than other banks. The ABS bought by banks that arbitrage risk weights, promise an as much as four times higher return on required capital than the ABS bought by other banks.

Nichttechnische Zusammenfassung

Fragestellung

Die Finanzkrise von 2007 bis 2009 hat ernsthafte Zweifel an der Effektivität des Basel II Regelwerks zur Behandlung von Verbriefungen geweckt. Der Basler Ausschuss für Bankenaufsicht selbst hat 2014 die "mechanische Abhängigkeit von externen Kreditratings" sowie eine "unzureichende Risikosensitivität" als zwei grundlegende Schwachpunkte des Regelwerks identifiziert. Wie weit Banken diese Schwachpunkte tatsächlich ausnutzen, um regulatorische Kapitalanforderungen zu umgehen, ist jedoch weitgehend unbekannt. Diese Studie geht dieser Frage nach und analysiert das Ausmaß der Arbitrage von regulatorischen Risikogewichten für forderungsbesicherte Wertpapiere (englisch Asset-Backed Securities, kurz ABS).

Beitrag

Das weitgehende Fehlen von Daten zu den Wertpapierpositionen institutioneller Investoren hat eine Analyse der Nachfrageseite des ABS-Marktes bisher verhindert. Ich nutze die Depotstatistik der Deutschen Bundesbank, welche die Bilanzpositionen von Banken mit Sitz in Deutschland disaggregiert für einzelne Wertpapiere berichtet. Ich analysiere die ABS-Investionen mit externen Kreditratings, um die Arbitrage von regulatorischen Risikogewichten auf der Nachfrageseite des ABS-Marktes aufzudecken.

Ergebnisse

Die Analyse legt nahe, dass Banken die Klassifizierung von ABS in grobe Risikoklassen ausnutzen, um regulatorische Eigenkapitalanforderungen zu reduzieren. Innerhalb jeder Risikoklasse kaufen Banken die ABS mit der höchsten Rendite und den schlechtesten Kreditsicherheiten. Dieses Ergebnis stützt die Hypothese, dass die Attraktivität von strukturierten Produkten teilweise durch Anreize zur Kapitalarbitrage erklärt werden kann.

Zweitens scheint die Arbitrage von Risikogewichten insbesondere von den Banken betrieben zu werden, deren Eigenkapitalausstattung sich nahe der regulatorischen Mindestanforderung bewegt. Für die Stabilität des Finanzsystems ist dieses zweite Ergebnis bedenklich, da gerade diese vermutlich anfälligeren Banken versuchen höhere Kapitalanforderungen zu umgehen.

Drittens, Banken mit niedriger Eigenkapitalquote kaufen *riskantere* ABS mit *niedrigeren* Kapitalanforderungen als Banken mit einer hohen Eigenkapitalquote. Die Rentabilität auf das regulatorisch geforderte Eigenkapital für den Kauf einer ABS ist bis zu viermal höher als im Fall von ABS, die von gut kapitalisierten Banken gekauft werden.

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 those banks operating with tight regulatory constraints pick the securities with the highest yield and lowest collateral quality among ABS with the same regulatory risk weight. This ABS selection allows banks to increase the return on the capital required for an ABS investment by a factor of four.

Keywords: Regulatory arbitrage, asset-backed securities, risk-taking, credit ratings

JEL classification: G01, G21, G24, G28.

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1 Introduction

The 2007–2009 financial crisis has raised fundamental questions about the effectiveness of bank regulation. In particular, the Basel II Securitization Framework, which regulates bank investments into asset-backed securities (ABS), has been subject to extensive review.[1] The Basel Committee on Banking Supervision (2014) has identified "mechanic reliance on external ratings" and "insufficient risk sensitivity" as two major weaknesses of the framework. Yet, the full extent to which banks actually exploit these shortcomings and evade regulatory capital requirements is not known. As disaggregated data on bank investments is publicly unavailable, *bank demand* for ABS has remained a black box.

I explore a unique data set maintained by the Deutsche Bundesbank (German Central Bank), which records the on-balance sheet holdings of banks in Germany *on a security-by-security basis*.[2] The high level of resolution allows me to study how regulatory arbitrage considerations influence the selection of individual ABS with an external credit rating. My analysis shows that the presumably most fragile banks in particular exploit the low risk sensitivity of the Securitization Framework and reach for yield in the very asset class that was at the core of the financial crisis. More importantly still, I estimate *the extent* to which banks exploits the low risk sensitivity of regulatory risk weights for rated ABS. Careful asset selection can increase the return on the equity required for an ABS investment by a factor of four.

Under Basel II, minimum capital requirements are calculated as 8% of risk-weighted assets. In the Securitization Framework, the risk weights depend on external credit ratings. ABS with the same rating usually have the same risk weight although the collateral, credit enhancement levels, and deal structures of the ABS can be very different. In each risk weight category (rating bucket) banks can thus choose from a variety of different risk-return profiles without altering their capital requirements.[3] By picking the securities with the highest yields in each risk weight category, banks can arbitrage capital requirements—a strategy called reaching for yield (Becker and Ivashina, 2014).

I test for such risk weight arbitrage in the following way. For each bank-security pair I model the probability that the bank acquires the ABS as a function of bank and security characteristics. I control for the risk weight of ABS when estimating the marginal effect of the yield spread on the probability that an ABS is acquired. I find that an increase of the yield spread by one percentage point increases the purchase probability for an ABS in a given risk weight category by 34% relative to the sample average. Banks prefer to buy the risky high-yield ABS in each risk weight bucket.

Which banks arbitrage risk weights most aggressively? A short portfolio optimization model, as in Glasserman and Kang (2014) and Rochet (1992), predicts that banks respond to a binding regulatory constraint by investing more into securities with a high ratio of return over risk weight. Consistent with this prediction, I find that banks with low

[1] 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.).

[2] My regression sample covers only banks residing in Germany and the period 2007–2012.

[3] For example, the base risk weight for a AAA rated ABS is 12% under the internal ratings-based approach (IRB) and entails a capital requirement of 1 cent for each Euro invested (€1.00 × 12% × 8%). But the yield spreads of AAA rated ABS have a standard deviation of 54bps in my sample, which reflects a large range of risk choices.

regulatory capital adequacy ratios (CARs), defined as bank equity over total risk-weighted assets, reach for yield more aggressively.[4] For a CAR close to the regulatory minimum requirement of 8%, an increase of the yield spread by one percentage point almost doubles the probability that the bank buys an ABS in a given risk weight bucket. The share of the ABS in the portfolio of a bank with a binding constraint increases by 1.5%. For higher CARs (laxer regulatory constraints) the effect decreases rapidly and becomes statistically insignificant for CARs above 17%. From a financial stability perspective this finding is problematic as it is precisely the undercapitalized and presumably most fragile banks that evade the regulation designed to constrain them.

I quantify the effect of regulatory arbitrage on the risk of banks' ABS positions. I compare the ABS investments of those banks that have tight regulatory constraints and arbitrage regulation with the ABS bought by banks with lax regulatory constraints. I find a striking mismatch between the average systematic risk (as proxied by the yield spread) and the average risk weight of the ABS. Banks with low CARs buy significantly riskier ABS with, on average, 25bps *higher* yield spreads. Yet, the higher systematic risk is not matched by higher capital requirements. The ABS bought by banks with low CARs have a 60% *lower* risk weight than the ABS bought by banks with high CARs. Exploiting this mismatch between risk weights and yield spreads is highly profitable. A simple back-of-the-envelope estimation shows that the ABS investments of banks with tight regulatory constraints promise a return on required equity approximately four times higher than the ABS bought by banks with lax regulatory constraints.[5] Assuming that the higher return on equity reflects a significant increase in bank risk, risk weights for rated ABS appear largely ineffective.

The high profitability of arbitraging the Basel Securitization Framework is made possible by the low yield-sensitivity of capital requirements. ABS with high yields can receive disproportionately low capital requirements because ABS risk weights rely on credit ratings, which are designed to capture *physical* default probabilities but not *systematic* risk. Yet, systematic risk is particularly high for ABS (Coval, Jurek, and Stafford, 2009).[6] Second, low rating standards in the ABS market reduce the risk-sensitivity of risk weights further as "the emphasis placed on credit ratings within the Basel Securitization Framework resulted in rating agency errors flowing through to regulatory capital requirements (Basel Committee on Banking Supervision, 2012)." The low sensitivity of ratings to systematic risk allows cases in which some ABS have higher yields but lower risk weights than other ABS. I identify these "misclassified" securities and find that banks with tight regulatory constraints in particular exploit risk weight bias of ABS.

[4] The CAR is lagged by three months so that ABS purchases do not alter it mechanically.

[5] Banks with a (tight) CAR equal to 9% invest into ABS with a risk weight of, on average, 30% and a yield spread of 112bps. Hence, they must hold 2.4 cents (= €1 × 30% × 8%) for each Euro invested. Banks with a (lax) CAR equal to 20% invest into ABS with a risk weight of, on average, 90% and a yield spread of 87bps. Hence, they must hold 7.2 cents (= €1 × 90% × 8%) for each Euro invested. Under the assumption that the cost of debt correspond roughly to the reference rate that an ABS earns in addition to the yield spread, the average returns on equity are approximately $\frac{€1 \times 1.12\%}{€0.024}$ and $\frac{€1 \times 0.87\%}{€0.072}$ for CARs equal to 9% and 20%. Details of this approximation are found in Section 6.4.

[6] Iannotta and Pennacchi (2012) show how rating-contingent regulation subsidizes systematic risk-taking. The Basel Committee on Banking Supervision (2012) has voiced concerns that "many models (of credit rating agencies) severely underestimated the concentration of systemic risk through securitization and resecuritization."

Most of my analysis uses yield spreads as a measure of systematic risk that is priced by the market. But relying on prices as a risk measure has several shortcomings. First, regulators might not care about systematic risk priced by investors but only about credit risk or physical default probabilities. Second, there might be concerns about mispricing or the possibility that bank demand for some ABS could feed back into yield spreads. Therefore, I also look at an alternative risk proxy. Collateral delinquency is an important measure for the quality of the collateral that is securitized. It should reflect the credit risk or the physical default risk of the collateral and does not rely on prices. I also control for different forms of credit enhancement as issuers might compensate lower collateral quality by writing bond insurance or increasing subordination levels. I find that my results are robust to using collateral delinquency as a risk proxy. Banks with high CARs shun the 'lemon' bonds with high credit risk in a given risk weight bucket. By contrast, banks with tight regulatory constraints invest relatively more into ABS with delinquent collateral.

A limitation of my analysis is that it does not explain *why* some banks operate with tight regulatory constraints and arbitrage ABS regulation. A low CAR (a tight regulatory constraint) could be due to an exogenous shock to bank capital or the outcome of an endogenous choice. I include bank fixed effects to control for *time-invariant* bank characteristics which might drive CARs and regulatory arbitrage incentives simultaneously. In some specifications, I use high bank leverage as a *time-varying* proxy for agency conflicts like risk-shifting (Jensen and Meckling, 1979 and Admati, DeMarzo, Hellwig, and Pfleiderer, 2011). However, I find only weak evidence that risk weight arbitrage is more prevalent among banks with high leverage, defined as equity over *unweighted* assets. Only banks that are highly leveraged in the *regulatory* sense, i.e. banks with low equity over *risk-weighted* assets, have a higher propensity to buy the high-yield ABS in each risk weight category.[7] In all regressions I control for bank size and, indeed, larger banks tend to reach more for yield in the ABS market.[8] This is consistent with existing studies which show that large banks are also more likely to implement other arbitrage strategies.[9]

The Basel III Securitization Framework is unlikely to resolve the problems uncovered in this paper. ABS risk weights will still depend on ratings, but ratings will be supplied by the banks themselves rather than by the credit rating agencies. Yet, it is at best questionable whether bank-supplied risk estimates, so called "internal ratings", are really more risk-sensitive than external credit ratings. While the Basel Committee has introduced a bank-wide minimum leverage ratio as a backstop against regulatory arbitrage, this risk-insensitive leverage restriction will potentially penalize relatively safe bank investments.[10] My findings suggest a radically different approach which is to calibrate ABS risk weights on market measures of risk like yield spreads.[11]

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 four papers that use firm-level data on ABS holdings and the first paper to provide micro-level evidence

[7]In my sample, the correlation between the CAR (equity over risk-weighted assets) and the leverage ratio (equity over *unweighted* assets) is only 0.16. Hence, the unweighted leverage ratio seems to be a poor proxy for regulatory constraints but should still capture risk-shifting incentives.

[8]All my results are also robust to controlling for different proxies of bank sophistication.

[9]E.g. Acharya, Schnabl, and Suarez (2013) show that exposure to asset-backed commercial paper conduits (ABCPs) correlates with bank size.

[10]Under Basel III bank equity over total *unweighted* bank assets must be at least 3%.

[11]See also Rochet (1992).

for risk weight arbitrage by banks. Merrill, Nadauld, and Strahan (2014) and Chernenko, Hanson, and Sunderam (2014) study insurance companies and 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. (2014) find that securitization exposures are highest among large insurers and insurers whose fixed income portfolios were managed by external managers. Mutual funds are shown to invest less if fund managers experienced losses in 1998. Erel, Nadauld, and Stulz (2014) estimate the ABS holdings for a cross-section of US banks using FR-Y9C data. They find 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 et al. (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.[12]

A number of other papers have also studied regulatory arbitrage but focus on different asset classes, investor groups, or regulatory frameworks. Becker and Ivashina (2014) use a methodology similar to mine. They 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. Like me, Behn, Haselmann, and Vig (2014) also study the inadequacy of Basel II risk weights but focus on the use of banks' own loan risk estimates for the calculation of capital requirements under the internal ratings-based approach (IRB). The authors use data from the German credit register to show that capital requirements decrease once their loans are regulated under the IRB approach. Mariathasan and Merrouche (2014) provide similar evidence showing that weakly capitalized banks manipulate Basel risk weights under the IRB approach in countries with weak bank supervision.

Finally, this paper also contributes to the debate whether regulatory arbitrage motives or investor naivety better explains why institutional investors buy risky ABS with overly favorable credit ratings. My findings are more consistent with the "regulatory arbitrage" hypothesis, according to which investors readily buy ABS as long as inflated ratings sufficiently relax regulatory constraints (Acharya and Richardson, 2009; Calomiris, 2009; Efing, 2014; and Opp, Opp, and Harris, 2013). My findings are less consistent with the "investor naivety" hypothesis according to which investors simply lack the expertise to understand the complex design of ABS and do not anticipate ratings inflation (Blinder, 2007; Skreta and Veldkamp, 2009; and Bolton, Freixas, and Shapiro, 2012).

The remainder of this paper is organized as follows. Section 2 reviews the Basel II Securitization Framework. Section 3 presents a theoretical model and its predictions. The

[12]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.

data and methodology are described in Sections 4 and 5. Section 6 presents the empirical findings, Section 7 their robustness, and Section 8 discusses the policy implications.

2 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 uses the SA or the IRB approach for the underlying collateral.

Credit ratings issued by external credit assessment institutions (ECAIs) are primarily used under the SA whereas the banks that are authorized to use the IRB approaches generally produce their own internal ratings. However, the Basel II Securitization Framework is an exception to this rule as external credit ratings are also used under the IRB approach, mainly because the lack of statistical data for securitized products makes the use of internally generated ratings difficult (Basel Committee on Banking Supervision, 2009). Hence, credit ratings play a central role under both the SA as well as the IRB approach, which makes the securitization market the ideal testing ground for the role of credit ratings in regulatory capital arbitrage.

Table 1, 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.[14] The mapping under the IRB approach (Table 1, Columns (2)–(4)) differs in two ways.[15] 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]

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

[14] 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.

[15] Under the securitization framework the IRB approach is divided again into three (sub-) approaches. Among these, the ratings-based approach (Table 1, 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 only be applied when an external rating neither exists nor can be inferred. This paper analyzes only rated exposures.

[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.

3 Hypothesis development

According to the Basel Committee on Banking Supervision (1999), regulatory arbitrage is the ability of banks to "exploit divergences between true economic risk and risk measured under the [Basel Capital] Accord." The definition does not specify what is meant by "true economic risk." For most of this paper I focus on risk priced by the market and use yield spreads as a proxy for systematic risk. I hypothesize that banks exploit the coarseness of ABS risk weights and buy the ABS with the highest systematic risk (yield spreads) in each risk weight category. I use the simple portfolio optimization model analyzed, for example, in Glasserman and Kang (2014) and Rochet (1992) to show that such reaching for yield is stronger for banks with binding regulatory constraints.[17]

Assume a bank with risk aversion γ, which 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. 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.[18] 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 $\frac{1}{\gamma}\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}$.[19] 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 shares so that banks with binding regulatory constraints choose a different relative mix of securities than unconstrained banks. Rochet (1992, p.1155) shows that constrained banks reach for yield and invest more into the securities for which μ_i/w_i is highest. Only if risk weights are proportional to expected returns, regulation does not affect the relative mix of securities in the portfolio (Glasserman and Kang, 2014).[20] 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

$$R_i = \beta_i R_S + \epsilon_i \quad \text{with} \quad \mathbb{E}(\epsilon_i) = \mathbb{E}(\epsilon_i R_S) = \mathbb{E}(\epsilon_i \epsilon_j) = 0 \tag{3}$$

where R_S denotes the return of the systematic factor explaining ABS returns.[21] The

[17] For simplicity, I have omitted the short-selling constraints in Rochet (1992) in this model.

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

[19] 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.

[20] 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).

[21] 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

expected return μ_i, variance σ_i^2, and covariance $\sigma_{i,j}$ follow as

$$\mu_i = \beta_i \mu_S \ , \quad \sigma_i^2 = \beta_i^2 \sigma_S^2 + \sigma_{\epsilon,i}^2 \ , \quad \sigma_{i,j} = \beta_i \beta_j \sigma_S^2 \ . \tag{4}$$

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: $\frac{\partial\left(\frac{x_2}{x_1+x_2}\right)}{\partial\lambda} > 0$. See Appendix A.1.

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 $\left(\frac{\partial \beta_{PF}}{\partial\lambda} < 0\right)$.[22] 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 $\kappa = \mathbf{w}'\mathbf{x}$.

Proof: $\frac{\partial \beta_{PF}}{\partial\lambda} > 0$ as long as $\beta_3 < \frac{\beta_2^2 \sigma_{\epsilon,1}^2 + \beta_1^1 \sigma_{\epsilon,2}^2}{\beta_2 \sigma_{\epsilon,1}^2 + \beta_1 \sigma_{\epsilon,2}^2 < \beta_2} < \beta_2$. See Appendix A.2.

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.

Misclassification of securities as in Proposition 2 is likely to be a problem when risk weights depend on credit ratings. Ratings are designed to capture *physical* default probabilities and expected losses and therefore are not suitable measures of *systematic* risk (Iannotta and Pennacchi, 2012). Furthermore, ratings are "rated through the cycle" and

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.

[22] See Appendix A.2.

only adjust slowly, which should also reduce their sensitivity to systematic risk (Cornaggia and Cornaggia, 2013). The dependence of risk weights on ratings seems particularly problematic in the case of ABS. First, ABS have relatively high systematic risk compared to other forms of debt (Coval et al., 2009). Second, a large strand of literature has collected evidence of particularly low rating standards in the ABS market (Benmelech and Dlugosz, 2009; Ashcraft, Goldsmith-Pinkham, and Vickery, 2010; and Griffin and Tang, 2012), which can in part be explained by agency problems on the part of the rating agencies (He, Qian, and Strahan, 2012; Cornaggia and Cornaggia, 2013; and Efing and Hau, 2015). Low rating standards are likely to reduce the risk sensitivity of ABS risk weights further.

I sum up the predictions of Propositions 1 and 2:

> **Prediction 1:** In a group of ABS with the same risk weight, banks with tight regulatory constraints (CARs close to the 8% minimum requirement) are more likely to buy the securities with the highest yield spreads.
>
> **Prediction 2:** Banks with tight regulatory constraints build riskier ABS portfolios with higher portfolio yields but lower capital requirements than banks that are unconstrained by regulation.

Propositions 1 and 2 are formulated for banks with *binding* regulatory constraints. Yet, the predictions are made for banks with *tight* regulatory constraints.[23] 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, Fahlenbrach, and Stulz, 2014)."

Using yield spreads to measure systematic risk priced by the market has several shortcomings. In particular, 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. But I acknowledge that regulators might be most concerned about the *physical* probability of bank default. In that case it would be more appropriate to consider only the credit risk of bank assets and not their systematic risk as priced by the market. Therefore, I also analyze the delinquency rate in the collateral pools of ABS. This measure of collateral quality should mainly measure credit risk alone. To account for the possibility that low collateral quality is compensated by other ABS characteristics, I control as much as possible for different forms of credit enhancements.

A second shortcoming of using yield spreads to measure risk is their susceptibility to mispricing. For example, there might be feedback effects of regulation on prices. By systematically investing into the high-yield bonds within a group of ABS with the same risk weight, banks might drive up their prices.[24] For example, Stanton and Wallace (2013) provide evidence that demand-side distortions from regulation are reflected in the prices of highly rated commercial mortgage-backed securities (CMBS).[25] As collateral delinquency rates do not depend on ABS prices, this alternative measure is robust to mispricing.

[23] 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.

[24] This would reduce arbitrage benefits and, therefore, incentives for regulatory arbitrage.

[25] In the USA, capital requirements were loosened for highly rated CMBS in 2002. Stanton and Wallace (2013) document a subsequent decline in yield spreads of highly rated CMBS.

Prediction 3: In a group of ABS with the same risk weight, banks with tight regulatory constraints (CARs close to the 8%-floor) are more likely to buy the securities with the lowest collateral quality (highest collateral delinquency).

4 Data

4.1 German bank investment in asset-backed securities

The primary data set used in this paper is the securities holdings statistics which comprise the quarterly asset holdings of all commercial banks residing in Germany on a security-by-security basis since December 2005. 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, volume estimates in this paper should be considered as a lower bound.

The data set is limited to *on-balance sheet* holdings of ABS with an external credit rating whereas holdings in off-balance sheet vehicles or unrated ABS treated under the Supervisory Formula Approach are not analyzed. However, even the on-balance sheet holdings alone reach a significant volume of roughly €120bn in December 2009. The size of these on-balance sheet holdings is significantly larger than the off-balance sheet investments of German banks reported in Arteta, Carey, Correa, and Kotter (2013). The total size of securities arbitrage (SAVs), structured investment (SIVs), and hybrid vehicles sponsored by German banks reaches only US$ 102bn at its peak in Q2.2007.[26]

Figure 1 shows the German on-balance sheet holdings (nominal value) of the ABS aggregated by bank type as of December 2008. The holdings of big banks and other commercial banks combined 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 small.

Figure 2 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

[26] 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. Erel et al. (2014) document that, also in the USA, on-balance sheet holdings of ABS are larger than off-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.

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.

4.2 Regression sample

As savings and cooperative banks are by law geographically limited in their scope of activities (Kick and Prieto, 2014) and hold almost no ABS (Figure 1), I drop them from the sample. I also eliminate banks with total assets less than €10bn as of March 2007 unless they are Landesbanken.[27] 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 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 shortly after bond issuance is necessary because I only observe the "launch" credit ratings published at the date when a bond is issued but not any subsequent rating changes. As only young bonds acquired shortly after issuance are considered, I also rule out the risk that I might falsely report a new bond purchase if the bank simply moves an old bond from an off-balance sheet vehicle to its balance sheet. Focusing on trading during the first six months after bond issuance captures 82% of the entire investment volume.[28]

The analysis uses the yield spread to proxy the systematic risk of a bond (Predictions 1 and 2). 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.[29] To limit the influence of data outliers, which might be simple reporting errors, I winsorize the yield spreads at the 1% and 99%-quantiles of the distribution. Finally, 1,097 ABS lack data on one or more control variables and are dropped. The probit regressions used in Section 6 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.

4.3 Summary statistics

Table 2, Panel A reports summary statistics for the 58 banks at the trading dates of the 1,884 bonds in the final regression sample.[30] The average bank has total assets

[27] 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.

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

[29] Focusing on bonds denoted in Euros loses only the 4% of on-balance sheet holdings that account for ABS with American collateral (Figure 1).

[30] 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.

worth €92.4bn but bank size exhibits considerable variation with a standard deviation of €123.6bn. The CAR, defined as eligible regulatory capital over risk-weighted bank assets, is on average 15% with a large standard deviation of 6%. A considerable number of observations has a CAR close to the regulatory minimum of 8% as every tenth observation has a CAR below 10%. The leverage ratio of a bank is defined as book equity over total assets. Its sample mean is only 4% and thus almost four times smaller than the sample mean of the CAR. The difference between both variables is even more striking at the 10% quantile, which is 1.4% for the leverage ratio and seven times smaller than for the CAR. The correlation between CAR and leverage ratio is only 0.16 and illustrates that the leverage ratio is a bad measure for the tightness of regulatory constraints.

Table 2, Panel B reports bond characteristics at issuance for the 1,884 ABS in the final regression sample. The yield spread has a sample average of 100bps and a standard deviation of 109bps. All bonds are issued at par. The nominal maturity for the average bond is 34 years whereas the weighted average life is only 6.1 years.[31] 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.[32] Forty-seven percent of the bonds carry a *AAA* rating, only 4% carry a composite rating below investment grade (Table 2, Panel C). Finally, I extract US Libor rates from the Thomson Reuters Datastream to construct proxies for the shape of the term structure at the time of bond issuance (Table 2, Panel E). *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.

In a first test for yield-seeking, I compare the yield spreads of ABS bought by banks with different CARs. The average yield spread of ABS bought by banks with a (lagged) CAR above 10% is 68bps. Banks with a (lagged) CAR $\leq$ 10% buy ABS with an average yield spread of 153bps. The difference of 85bps 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.[33] In a second non-parametric test, I also compute the ratio *Yield Spread* over *Risk Weight* for each ABS. I find that banks with a lagged CAR $\leq$ 10% buy ABS with a high ratio *Yield Spread* over *Risk Weight* of, on average, 0.059. By contrast, banks with high CARs above 10% buy bonds with an average ratio of only 0.038. The difference is again statistically significant at the 1% level and suggests that banks with low CARs buy ABS with higher yields relative to their risk weights.

[31]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.

[32]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).

[33]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.

5 Methodology

5.1 Regression specification

I consider a probit model in which $I_{b,s}$ equals 1 if bank b invests into ABS s within six months after the issuance date of the security, 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. The conditional probability of security acquisition follows as

$$P(I_{b,s} = 1|\mathbf{X}) = \Phi(\beta\mathbf{X}). \tag{5}$$

To estimate the extensive margin of investment, I use the probit specification and model the conditional probability as the normal cumulative distribution function $\Phi(.)$ because it achieves the highest log pseudolikelihood. In Section 7 I show that the results do not change if I use the logit, linear probability, and complementary log-log forms of the conditional probability of security acquisition. To estimate the intensive margin of investment, I replace the binary investment dummy $I_{b,s}$ by the investment volume and estimate OLS and Tobit regressions. In all models I use the following specification of $\beta\mathbf{X}$:

$$\beta\mathbf{X} = \beta_1\ YS + \beta_2\ RWC + \beta_3\ Lag\ CAR + \beta_4\ Lag\ CAR \times YS + \beta_5\ Lag\ CAR \times RWC + \beta_{\mathbf{C}}\ C \tag{6}$$

where YS denotes the yield spread of the security, RWC is a vector of dummies for the different Basel II risk weight categories of securities, $Lag\ CAR$ is the lagged capital adequacy ratio of the bank and C is a vector of controls.

Identification for Prediction 1 is achieved through the two interactions $Lag\ CAR \times YS$ and $Lag\ CAR \times RWC$. The interaction $Lag\ CAR \times RWC$ controls for the probability that a bank with given $Lag\ CAR$ is more or less likely to buy a security belonging to a given risk weight category RWC. It captures any risk-taking *across* risk weight categories where a bank substitutes investment in one RWC for investment in another. The interaction $Lag\ CAR \times YS$ captures any remaining risk-taking that occurs *inside* risk weight categories. If banks with low capital adequacy ratios buy more ABS with yield spreads at the risky end of a given risk weight category, the interaction effect of $Lag\ CAR \times YS$ will be negative. To rule out that the acquisition of a security mechanically changes the risk-weighted assets and thereby the CAR of a bank, I lag the CAR by three months.

To control for bank size, I also include interactions of $Log\ Assets$ with YS and RWC:

$$\begin{aligned}\beta\mathbf{X} = {} & \beta_1\ YS + \beta_2\ RWC + \beta_3\ Lag\ CAR + \beta_4\ Lag\ CAR \times YS + \beta_5\ Lag\ CAR \times RWC \\ & + \beta_6\ Log\ Assets + \beta_7\ Log\ Assets \times YS + \beta_8\ Log\ Assets \times RWC + \beta_{\mathbf{C}}\ C.\end{aligned} \tag{7}$$

If larger banks are more likely to seek high yields within a given group of ABS with the same risk weight, the interaction effect $Log\ Assets \times YS$ will be positive.[34]

Among the control variables C are also the two proxies for the level and the slope of the

[34] In unreported regressions I also control for the size of a bank's total ABS holdings, the amount of collateral that the bank securitizes itself, or for the amount of derivatives trading. These controls might be interpreted as proxies for bank sophistication. My results remain qualitatively unchanged.

term structure at the time of bond issuance (see Section 4.3) as well as dummy variables for issuance years. These variables control for market-wide interest rate fluctuations and ensure that yield spreads of bonds acquired in different years remain comparable.[35] The set of bond variables comprises two controls for the nominal maturity and the weighted average life, *Log Bond Size*, as well as dummy variables for the different ABS types shown in Figure 2. As the bonds bought by banks with low CARs or high bank size might be systematically different from the bonds purchased by well-capitalized and small banks, I also include interaction terms between the bond controls and *Lag CAR* and *Log Assets*:

$$\begin{aligned}\beta\mathbf{X} = &\beta_1\ \mathit{YS} + \beta_2\ \mathit{RWC}\\ &+ \beta_3\ \mathit{Lag\ CAR} + \beta_4\ \mathit{Lag\ CAR} \times \mathit{YS} + \beta_5\ \mathit{Lag\ CAR} \times \mathit{RWC}\\ &+ \beta_6\ \mathit{Log\ Assets} + \beta_7\ \mathit{Log\ Assets} \times \mathit{YS} + \beta_8\ \mathit{Log\ Assets} \times \mathit{RWC}\\ &+ \beta_9\ \mathit{Controls} + \beta_{10}\ \mathit{Lag\ CAR} \times \mathit{Controls} + \beta_{11}\ \mathit{Log\ Assets} \times \mathit{Controls}\end{aligned} \quad (8)$$

I estimate the β-coefficients in Eq. (8) using the probit specification for the probability that bank b buys security s. The marginal effect of regressor x_j is defined as

$$\frac{\partial P(I_{b,s} = 1|\mathbf{X})}{\partial x_j} = \phi(\beta\mathbf{X}) \cdot \beta_j \quad (9)$$

where $\phi(.)$ is the probability density function of the normal. Since the marginal effect is conditional on the independent variables $\mathbf{X}$, I compute the average marginal effects:

$$\widehat{AME}_j = N^{-1} \sum_i \phi(\hat{\beta}\mathbf{X}_i) \cdot \hat{\beta}_j \ ^{36} \quad (10)$$

5.2 Determining risk weight categories

I determine the appropriate risk weight category *RWC* of a bond using Table 1, Column (3), and introduce dummies for rating buckets with the same IRB base risk weights. Choosing the IRB 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 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, 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 1, 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 base risk weights, which are different for *AAA* and *AA* rated securities, I cannot identify such risk-shifting from *AAA* to *AA* rated securities, only reaching for yield within the *AAA* and the *AA* category.

[35] Controlling for issuance years also absorbs changes in the liquidity of the ABS market.

[36] 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.

The second disadvantage of applying the IRB 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 1, 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*.[37]

6 Results

6.1 Reaching for yield and regulatory arbitrage

Table 3 reports the regression results of two probit models for the probability that a bank buys a given ABS. The pseudo R^2 are 0.23 and 0.28, respectively. A 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. The test cannot reject the null hypothesis that the models are correctly specified.[38]

In Model I of Table 3 I test whether banks are more likely to buy the high-yield bonds in a given risk weight category *RWC*. I condition on the *RWC* when estimating the effect of the bond yield spread on the probability that a bank buys the bond.[39] Columns (1) and (2) report the regression coefficients and average marginal effects of Model I.[40]

The yield spread of a bond has an average marginal effect of 0.096% on the probability of security acquisition and is statistically significant. ABS at the risky end of each risk weight category *RWC* are more likely to be bought than ABS that have relatively low yield spreads. Conditional on the *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%). This result suggests that banks exploit the coarseness of Basel II risk weights.

Next I verify whether risk weight arbitrage is more pronounced for banks with low CARs (Prediction 1). I estimate the interaction effect *Spread* × *Lag CAR* conditional on *RWC* × *Lag CAR*. Table 3, Column (1) shows that the regression coefficient of *Spread* × *Lag CAR* is negative and highly significant. Figure 3, Graph (1) illustrates how an increase of *Spread* by one percentage point increases the probability that a bank with given *Lag CAR* buys the ABS. The vertical axis shows the average marginal effect of *Spread* on the purchase probability for different values of *Lag CAR* on the horizontal axis.[41] Clearly,

[37]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.

[38]The test outcome is the same if the sample is divided into 10 or 20 subgroups.

[39]I also estimate Model I without controlling for *RWC*. Then the marginal effect of *Spread* measures yield-seeking *across* risk weight categories. The results can be found in Appendix B.1.

[40]Note that the average marginal effect and the coefficients need not have the same sign since all explanatory variables are also interacted with *Lag CAR* and *Log Assets*.

[41]In the literature two main approaches have emerged to show interaction effects between two variables in probit and logit models (Karaca-Mandic, Norton, and Dowd, 2012). The approach chosen in this paper computes adjusted predictions and marginal effects of the first variable at different values of the second variable (for example Williams, 2012; Canette, 2013; and StataCorp., 2013). Under the second approach

a higher yield spread does not significantly increase the probability that unconstrained 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%). For *Lag CARs* equal to 9% and 15% the marginal effect of a higher yield spread reduces to 0.190% and 0.079%, respectively. These marginal effects of the yield spread at *Lag CARs* equal to 8%, 9%, and 15% are significantly different from zero and from each other (see Appendix B, Table B.2). As stated in Prediction 1, 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.

Several studies have shown that regulatory arbitrage is more pronounced for larger banks. For example, Acharya et al. (2013) find that exposure to ABCPs correlates with bank size. Figure 3, Graph (2) shows that large banks are also more likely to arbitrage risk weight categories. Banks with high *Log Assets* are significantly more likely to buy an ABS if the security has a high yield spread relative to other ABS in the same *RWC*. The same is not true for small banks. A possible explanation could be that larger banks are more sophisticated. However, Figure 3, Graph (2) is robust to controlling for banks' own securitization activity, their derivatives-trading, or for their total ABS investment—three variables, which might be interpreted as proxies of bank sophistication. Another 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). ABS with high systematic risk in particular would be an attractive investment for too-big-to-fail banks because they typically default only during economic crises when the probability that systemic banks are bailed out is highest (Coval et al., 2009).

To control for unobserved bank heterogeneity, which could covary with incentives to arbitrage risk weight categories, I include bank fixed effects in Table 3, Model II. Hence, identification in Model II ignores cross-sectional variation and only compares the purchase decisions of a given bank as its *CAR* changes over time. However, the results of the bank fixed effects regression should be interpreted with caution. As some bank dummies perfectly predict the failure of the outcome variable $I_{b,s}$, controlling for bank fixed effects leads to the loss of 35 banks and the sample size reduces to 41,988 bank-security pairs.[42]

After the inclusion of bank fixed effects, the evidence for reaching for yield within risk weight categories becomes stronger. The average marginal effect of the yield spread

we compute the cross-partial derivative of the conditional probability with respect to the two interacted variables (see Ai and Norton, 2003 and Norton, Wang, and Ai, 2004). The first approach serves my purpose better as it shows the change of the average marginal effect of *Spread* across different values of *Lag CAR* and does not aggregate all information into one single number.

[42]A second concern could be that joint estimation of fixed effects and regression coefficients leads to inconsistent parameter estimates in non-linear panel models like the probit if the number of periods is small (Greene, 2004). However, in Table 3, Model II each of the 23 bank fixed effects is estimated based on almost 2000 (bond-)observations, which should attenuate any incidental parameter problem. Nevertheless, I also show OLS regressions in Section 7 to show the robustness of my results to a linear probability specification. Finally, all probit regressions are also estimated without bank fixed effects.

increases from 0.096% in Model I to 0.238% in Model II. Also the interaction effect of *Spread* × *Lag CAR* is much stronger in Model II. Figure 3, 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. 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.[43] By contrast, Figure 3, 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 very little over time. Overall, controlling for bank heterogeneity strengthens the evidence for Prediction 1.[44]

6.2 Regulatory arbitrage at the intensive margin

Until now I have modeled investment decisions as a binary variable $I_{b,s}$ equal to 1 if bank b buys ABS s. This approach has the disadvantage that it treats two bond purchases 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:

$$\textit{Standardized InvVol}_{b,s} = \frac{InvVol_{b,s}}{\sum_{i\in\Omega(b,s)} InvVol_i} \cdot 100\% \tag{11}$$

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 report the regression coefficients and average marginal effects of Tobit specifications in Table 4, Columns (1)–(4).[45] I include dummies for risk weight categories *RWC* as well as the interactions *RWC* × *Lag CAR* and *RWC* × *Log Assets*. Model IV also controls for bank fixed effects. The pseudo R^2 suggest that the Tobit models describe the data reasonably well. Figure 4 illustrates the negative interaction effect *Spread* × *Lag CAR* in both Tobit models. An increase of the bond yield spread by one percentage point increases the fraction of capital invested in the ABS by about 1.5% for a bank operating with a CAR at the regulatory 8%-floor. Consistent with Prediction 1, the average marginal effect of the yield spread decreases for higher CARs and becomes statistically insignificant for *Lag CAR* $\geq$ 16%.

6.3 Regulatory arbitrage and 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 (e.g. Jensen and Meckling (1979) and Admati et al. (2011)). In this section I analyze whether agency problems (e.g. risk shifting) alone are enough to explain the risk weight arbitrage documented in Section 6.1. We might imagine that, even in the absence of regulation, highly

[43] The statistical significance of the differences between the average marginal effects of *Spread* at different *Lag CAR* is shown in Appendix B, Table B.2.

[44] In unreported regressions, I rerun Model I using the same sample as in Model II. The average marginal effects are close to those shown in Table 3, Column (2). Therefore, the different marginal effects in Model I and II do not seem to be due to sample differences.

[45] The marginal effects are computed for the left-truncated mean ($\partial E[y|x, y > 0]/\partial x$). In Appendix B.5 I also estimate Tobit regressions with the log investment volume as well as OLS regressions.

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 book equity over total assets. Both variables are only weakly correlated (Section 4.3). 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 3 using the leverage ratio instead of *Lag CAR*. Figure 5, 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 5, 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 bank leverage alone cannot explain the risk weight arbitrage documented in Section 6.1.

6.4 Capital adequacy and regulatory effectiveness

According to Prediction 2, banks with tight regulatory constraints will build portfolios with higher systematic risk but lower capital requirements. To test this hypothesis, I use the coefficient estimates from Model I (Table 3, Column (1)) to predict the yield spread and risk weight of the *average* ABS bought by a bank with a given CAR.[46] Figure 6 shows the yield spread (solid line) and risk weight (dashed line) of the average ABS bought by banks with different CARs. Clearly, unconstrained banks buy less risky ABS with lower yield spreads than constrained banks that operate with CARs close to the 8% minimum requirement. If Basel regulation worked effectively, ABS investments with higher systematic risk (and thus higher yield spreads) should be associated with higher capital requirements. The risk weight (dashed line) should be downward-sloping like the solid line. Yet, this is not the case. On the contrary, constrained banks (with low CARs) succeed in increasing asset risk while at the same time economizing on regulatory capital.

For example, a bank with a *Lag CAR* equal to 20% buys ABS with a risk weight of, on average, 90% 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 30% but a high yield spread of 112bps. This example suggests that banks with tight regulatory constraints load more on systematic risk than other banks but do not incur higher capital requirements.

The risk weight arbitrage implemented by banks with low CARs is highly profitable. In the example above, the average risk weight of 30% corresponds to a capital requirement of

[46] I cannot analyze banks' entire ABS portfolios because I do not observe the risk weight categories and yields of "grown-up" positions due to missing time series data. Therefore, I compare the yield spread and risk weight of the *average* ABS bought by banks with tight and lax regulatory constraints. See Appendix B.2 for details on how the coefficient estimates from Model I are used to compute the average yield spreads and risk weight categories of ABS bought by banks with different CARs.

only 2.4 cents (= €1 × 30% × 8%) for each Euro invested. By contrast, the bank with the high *Lag CAR* equal to 20% must hold 7.2 cents (= €1 × 90% × 8%) against each Euro invested. The three times higher leverage together with the higher yield spread translates into a roughly four times higher promised return on equity $\left(\approx \frac{€1\times 1.12\%}{€0.024} \;/\; \frac{€1\times 0.87\%}{€0.072}\right)$.[47] Under the assumption that a higher return on equity reflects higher bank risk, this result suggests that the Basel II regulation of ABS investments is largely ineffective.

6.5 Risk weight classification bias

In the previous section I showed that banks that reach for yield buy, on average, riskier ABS without incurring higher capital requirements and thereby increase the return on required capital. In the theoretical model presented in Section 3 this is possible if risk weights are not monotonically increasing in systematic risk. In this section I will identify all securities that are misclassified in the sense that they have lower risk weights but (much) higher yield spreads than other ABS. In a second step I show that 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.[48] The variable has a median of zero, a mean equal to 18bps and a standard deviation of 48bps (see Table 2).

Table 5 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 securities assigned to a wrong RWC. In particular, banks with tight regulatory constraints buy the misclassified securities. Figure 5, Graphs (3) and (4) show that the average marginal effect of *Risk Weight Bias* decreases monotonically over *Lag CAR* in regression specifications with (Graph 4) and without bank fixed effects (Graph 3). For a bank with a *Lag CAR* of 8% an increase of *Risk Weight Bias* by one standard deviation (0.48%) increases the probability of security acquisition by 0.180% (Graph 3) or 0.949% (Graph 4).

6.6 Collateral quality and regulatory arbitrage

In this section I replace yield spreads by collateral delinquency rates, which are not susceptible to mispricing. Furthermore, collateral delinquency should measure the *physical* default risk or credit risk of ABS, which might be of most concern to the regulator.

I use a sample of 1,529 ABS for which Moody's database "Performance Data Services" has information on the 90 days delinquency rate measured in collateral pools nine months after bond issuance.[49] In addition to the bond controls in previous specifications,

[47] 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 $\frac{Spread}{c}$.

[48] The yield spreads are corrected for the variation explained by bond controls like maturity, bond size, issuance year etc. before *Risk Weight Bias* is calculated. See Appendix B.3 for details.

[49] See Appendix B.4 for details about the delinquency data and the bond sample.

I also control for the combined face value of subordinated deal tranches that serves as a loss cushion to a given security in a 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 bond controls mitigate concerns that lower collateral quality (higher delinquency rates) is compensated by some kind of credit enhancement.

Table 5, Model VII reports the coefficients and average marginal effects of a probit specification without bank fixed effects. Conditional on the risk weight category of a given ABS, the delinquency rate of its collateral has a statistically significant average marginal effect of −0.027%. An increase of the delinquency rate by one standard deviation (= 2.00%) reduces the purchase probability by 0.054%, which corresponds to a reduction by 31% relative to the sample average (= 0.173%). On average banks are less likely to buy ABS backed by higher amounts of delinquent collateral within a given risk weight category. Figure 5, Graph (5) shows the interaction effect of *Delinquency* × *Lag CAR*. 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 at the 1% level for *Lag CAR* above 11%.[50] Banks operating with CARs close to the regulatory minimum buy ABS backed by high- and low-quality collateral with equal probability. By contrast, banks with high CARs tend to select the ABS backed by high-quality collateral within a given risk weight category.

Table 5, Model VIII has the same specification as Model VII except that it controls for bank fixed effects. As the probit regression drops 40 banks, leaving only a sample of 18 banks and 27,289 bank-bond pairs, the following results should be interpreted with caution. The average marginal effect of *Delinquency* is −0.11% and five times larger than in Model III (in absolute terms). Figure 5, Graph (6) shows that the average marginal effect of *Delinquency* remains negative and statistically significant for banks with high CARs. At low values of *Lag CAR* the average marginal effect becomes positive. One-sided tests confirm that the average marginal effect of *Delinquency* at a *Lag CAR* equal to 8% is significantly larger than the average marginal effect at higher values of *Lag CAR*.[51] In a given risk weight category, banks with low CARs invest a higher fraction of their capital into the ABS backed by low-quality collateral than unconstrained banks (Prediction 3).

7 Robustness

In this section I establish the robustness of my findings to alternative specifications of the conditional purchase probability in Eq. (5) and to different regression samples.

Table 6, Columns (2) and (4) report the average marginal effects of the logit and the complementary log-log model, respectively.[52] The average marginal effects of *Log Assets*,

[50] 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).

[51] The p-values for the one-sided test range between 0.08 and 0.02.

[52] The logit and probit models usually report similar marginal effects except in the tails of the conditional probability function. Different regression coefficients are due to a different scaling but do not have different implications on their own. The complementary log-log model is sometimes recommended when the distribution of the dependent variable is skewed such that there is a relatively large proportion of one possible outcome (Cameron and Trivedi, 2005).

Log CAR, *Spread*, and the bond controls are very close to those shown for the corresponding probit specification in Table 3, Column (2). Figure 7 shows that the interaction effects *Spread* × *Lag CAR* estimated in the logit and complementary log-log model are almost identical to the baseline estimate illustrated in Figure 3, Graph (1). The log pseudolikelihood is slightly higher for the probit specification used in Section 6 (−1509.2) than for the logit (−1511.6) and the complementary log-log model (−1511.9).

In Table 6, Column (5) I report the marginal effects of a linear probability model, even though this specification is conceptually flawed.[53] The linear probability model is estimated in an ordinary least squares regression. The interaction effect *Spread* × *Lag CAR* is −0.504% and statistically significant at the 10% level. Table 6, Column (6) reports the marginal effects of an OLS regression that allows for non-linearities. It includes interactions between the yield spread and dummy variables for banks with a *Lag CAR* below the 10%-quantile, between the 10%- and the 25%-quantile, between the 25%- and the 50%-quantile, and above the 50%-quantile. The interaction of *Spread* × Dummy(*Lag CAR* < Q10) has a marginal effect of 0.213%, which corresponds roughly to the average marginal effect of *Spread* that the probit model reports at *Lag CAR* values of 8% and 9% (see Figure 3, Graph (1)).

The model in Rochet (1992) predicts that banks with tight regulatory constraints shift investment to assets with a high expected return relative to their risk weight. In Appendix B.6, I replace the yield spread and the risk weight dummies with the ratio *Spread/Risk Weight* and estimate the probit regressions again. Results remain qualitatively unchanged. My results are also robust to limiting the regression sample to only *AAA* rated ABS (Appendix B.7).[54] Finally, I check the robustness of the Tobit regressions for the share of capital that a bank invests into a given ABS. In Appendix B.5, 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 B.5).

8 Conclusion

I analyze the demand-side of the securitization market using unique data on bank holdings of ABS. I find that banks that operate with capital adequacy ratios close to the regulatory 8%-floor exploit the low risk sensitivity of rating-contingent ABS risk weights. These banks with tight regulatory constraints pick the ABS with the highest yields and the lowest collateral quality in a given group of securities with the same Basel II risk weight. This reaching for yield allows them to buy riskier ABS and to increase the leverage of their investments. Their ABS investments promise a return on equity approximately four times higher than the ABS bought by banks with lax regulatory constraints.

Basel III, which will come into effect in January 2018, is unlikely to end risk weight arbitrage in the ABS market as the new Securitization Framework continues to rely on

[53] Assuming that a probability is linearly related to a continuous variable is conceptually problematic because continuously increasing the independent variables will drive $P(I_{b,s}|\mathbf{X})$ outside the interval [0,1].

[54] I also check if reaching for yield is more pronounced in some risk weight buckets than in others. However, given the small number of bonds in some risk weight buckets, *RWC*-specific estimates of reaching for yield are only measured with large error and, therefore, only reported in Appendix Figure B.3.

ratings. The risk sensitivity of risk weights might even decrease further relative to Basel II because the ratings will no longer be supplied by external credit rating agencies but by the banks themselves.[55] Banks will use their own IRB models to estimate risk parameters that describe the collateral of ABS (see Basel Committee on Banking Supervision, 2014). The bank-supplied risk parameters (e.g. estimates of the probability of default and loss-given-default) will then be mapped into "internal ratings" and determine the capital requirement for each securitization exposure.[56] This approach is problematic because banks can design and calibrate their IRB models to minimize their capital requirements (see Behn et al., 2014). The findings in this paper suggest an alternative way to compute capital requirements. Risk weights could be calibrated on market measures of systematic risk like yield spreads (see also Rochet, 1992).

[55] Under Basel II banks have to use the rating-contingent risk weights in Table 1 whenever an exposure is rated. Under Basel III banks will be allowed to use external ratings only if the bank has no (supervisory-approved) IRB model for the underlying collateral of the securitization or if the bank lacks the necessary data to apply the IRB model.

[56] The bank-supplied risk estimates will be used to compute the IRB capital requirement for the underlying exposures in the collateral pool. The final risk weight for the securitization exposure will be calculated with the simplified supervisory formula approach (SSFA). Under Basel II the supervisory formula approach is only allowed for unrated ABS.

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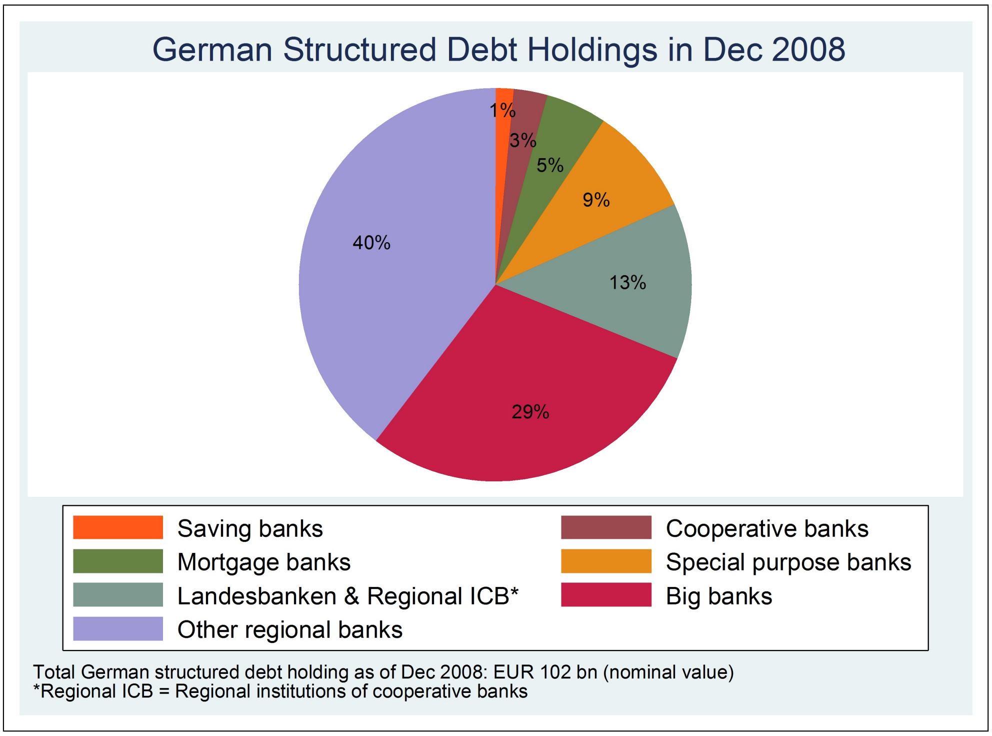

Figure 1: Shown are the German on-balance sheet holdings (nominal value) of asset-backed securities as of December 2008 aggregated by bank category. Total structured debt holdings as of December 2008 equal €102bn.

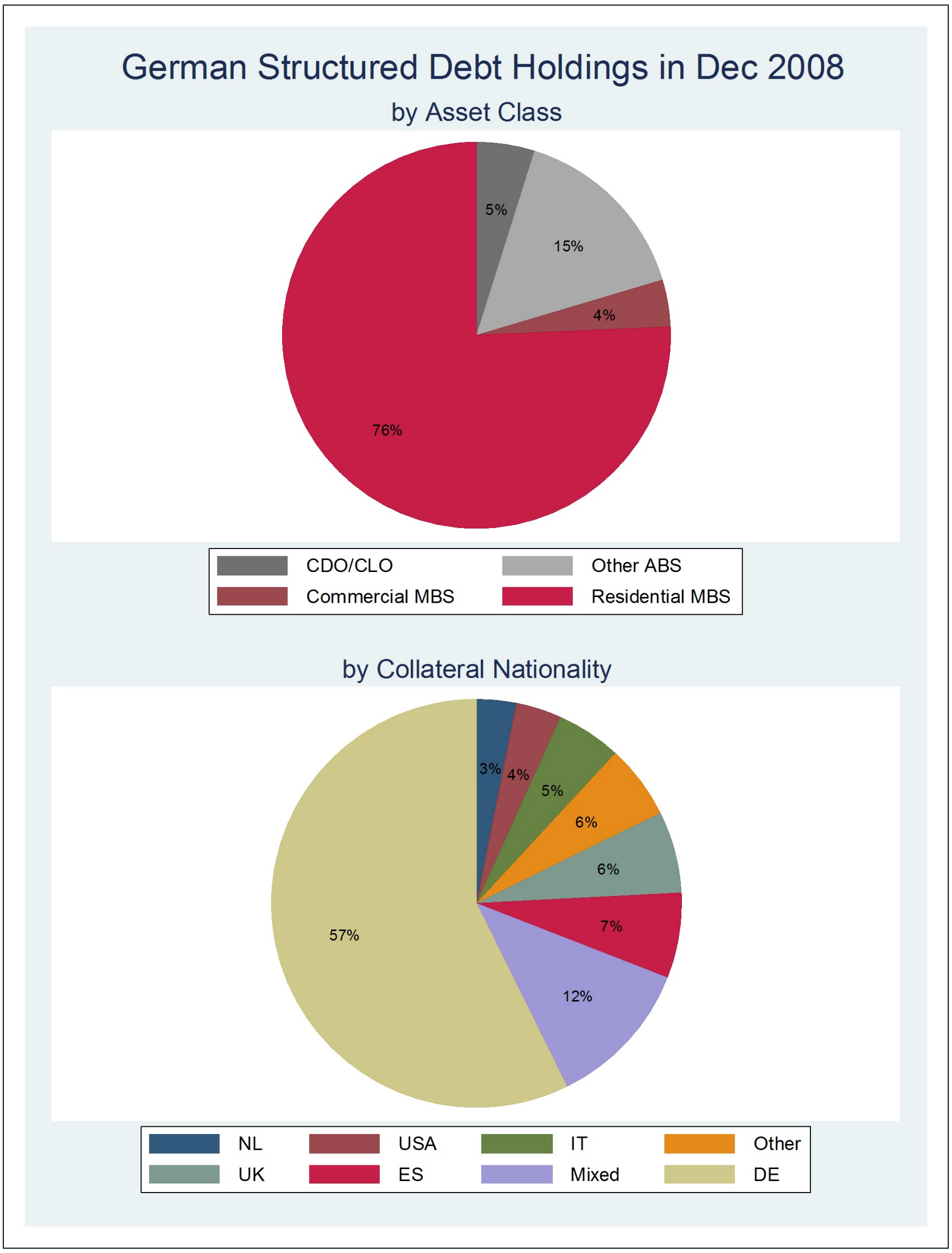

Figure 2: Shown is the composition of on-balance sheet structured debt holdings by German banks as of December 2008 by asset type and national origin of the collateral. Total German structured debt holdings as of December 2008 equal €102bn. The country abbreviations are: NL: Netherlands, USA: United States, IT: Italy, UK: United Kingdom, ES: Spain, Mixed: Mixed collateral origin, DE: Germany.

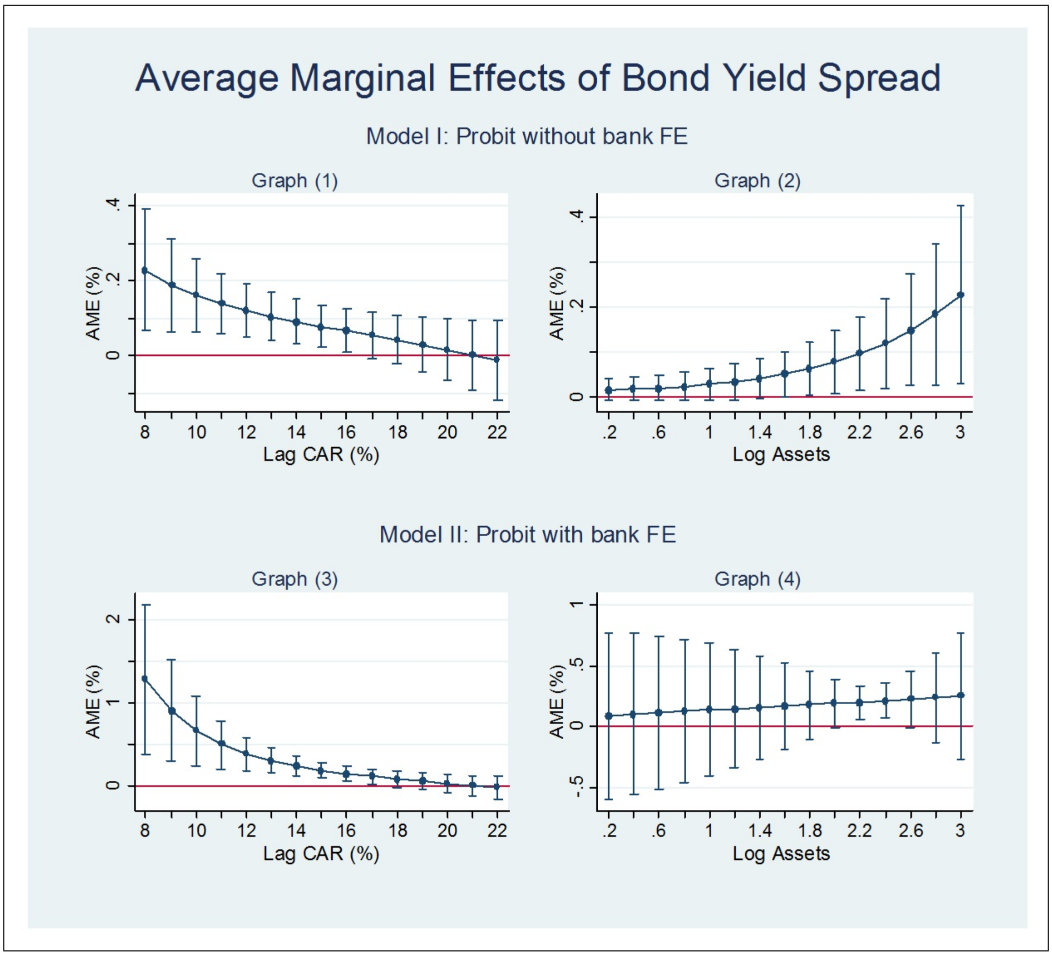

Figure 3: Graphs (1)–(4) illustrate whether banks with low capital adequacy ratios and large banks are more likely to buy the high-yield bonds in a group of ABS with the same risk weight. The vertical axis shows the average marginal effect of the bond yield spread on the probability that a bank with 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%, 90% quantile = 22%) and *Log Assets* (median = 1.43%, 90% quantile = 3.17%). Graphs (1) and (2) illustrate the interaction effects *Spread* × *Lag CAR* and *Spread* × *Log Assets* estimated in Table 3, Model I (without bank fixed effects). Graphs (3) and (4) correspond to Table 3, Model II (with bank fixed effects). Confidence intervals are drawn for the 5% level.

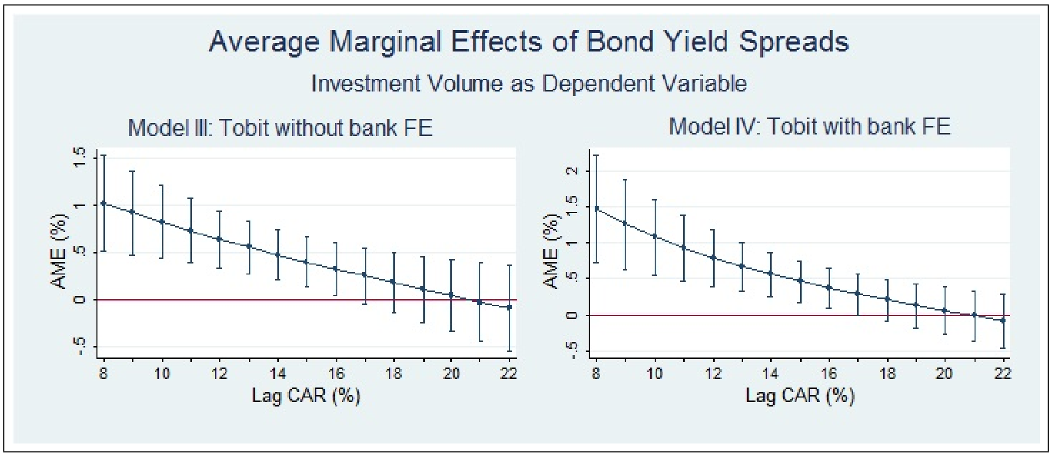

Figure 4: Both graphs show the average marginal effect of the bond yield spread on the (standardized) investment volume defined as the Euro-amount invested in the ABS as a fraction of total ABS investments by the bank. Model III is estimated without bank fixed effects and Model IV with bank fixed effects. Confidence intervals are drawn for the 5% level.

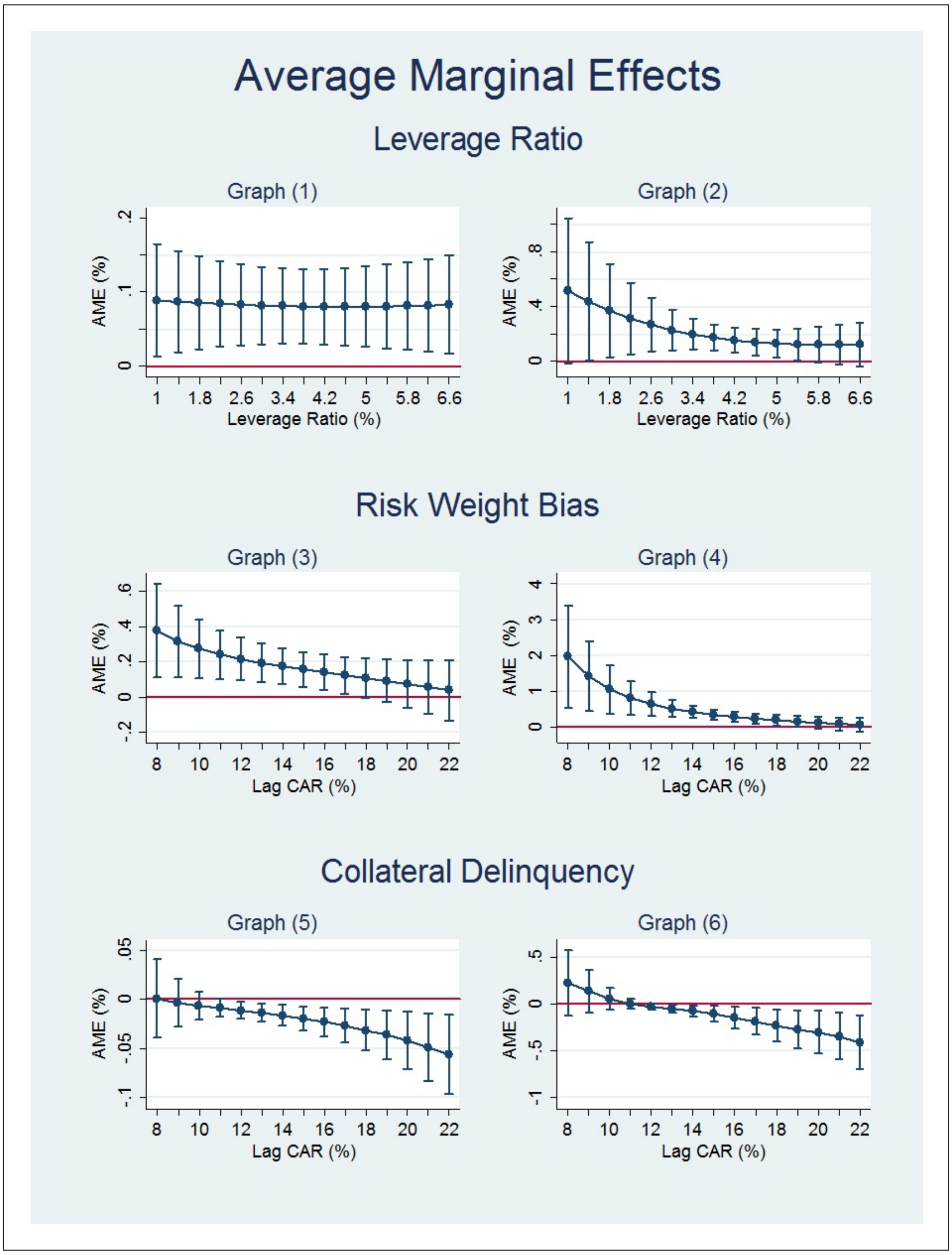

Figure 5: Graphs (1) and (2) show the average marginal effect of the bond yield spread on the probability that a bank with given *Leverage Ratio*, defined as book equity over total assets, buys the ABS. Graphs (3) and (4) show the average marginal effect of the *Risk Weight Bias* on the probability that 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.

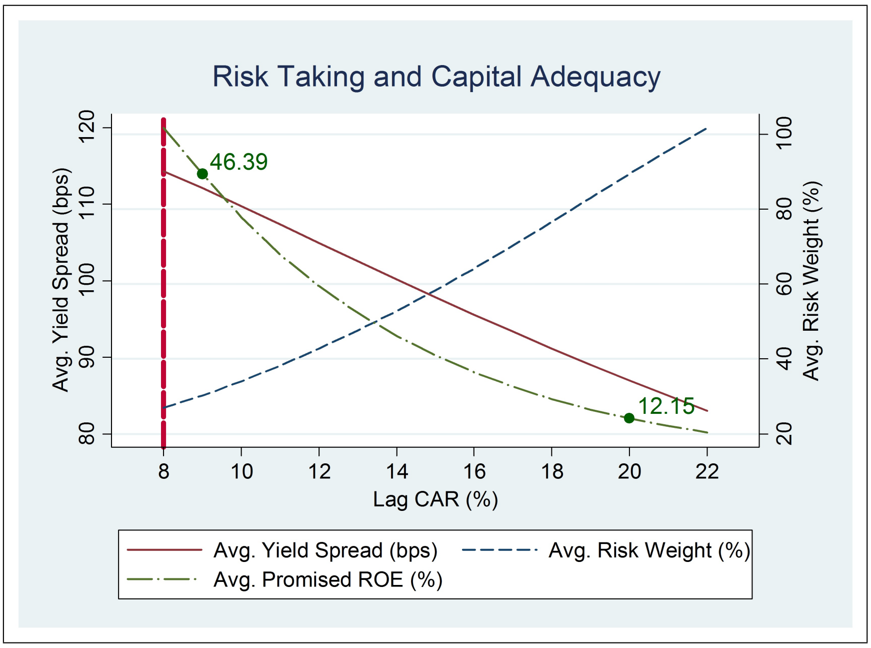

Figure 6: Shown are the predicted yield spread and regulatory risk weight for the average ABS bought by a bank with a lagged CAR equal to 8, 9, ..., 22%. Average risk weight and yield spread are estimated using the coefficients of Model I (see Table 3).

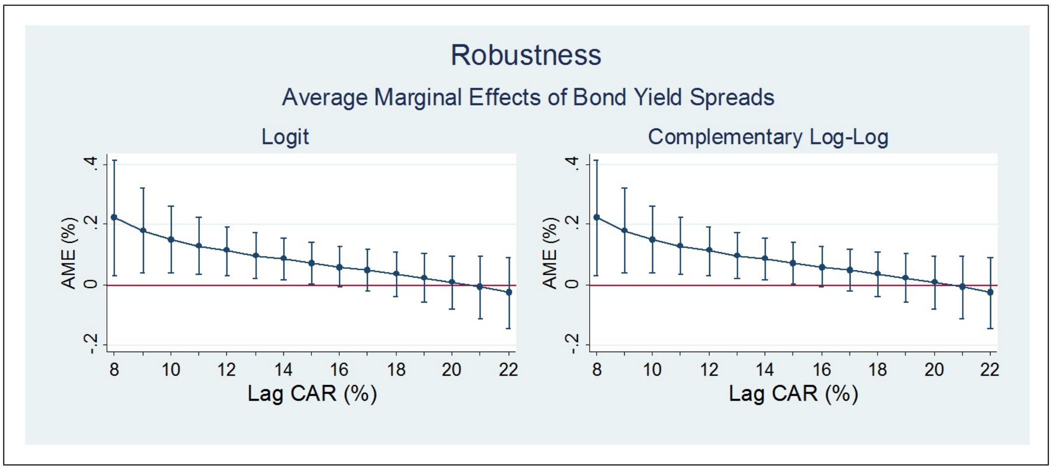

Figure 7: The two graphs show the average marginal effect of the bond yield spread on the probability that a bank with given *Lag CAR* buys the ABS. Neither the logit nor the complementary log-log specification controls for bank fixed effects. Confidence intervals are drawn for the 5% level.

Table 1: **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)–(4) show the risk weights for the internal ratings-based (IRB) approach for securitization exposures. 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 approach are defined by the ratings-based approach which is the relevant (sub-) approach under IRB that banks must apply to all rated securitization exposures.

	SA	IRB		
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 2: **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 in %	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	Definition Eq. (A.11), 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 US Libor	1,884	2.91	2.17	0.25	2.72	5.32
Term Structure Slope	12mth minus 1mth US Libor	1,884	0.42	0.63	−0.32	0.16	1.40

Table 3: **Bond purchase decisions 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. The independent variables are: *Lag CAR* = capital adequacy ratio lagged by one year-quarter; *Log Assets* = *Log*(*Bank Assets*); *Spread* = bond yield spread; *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; *RWC*, issuance year, and asset type dummies. 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)
Log Assets	−1.860***	0.266***	−3.278***	−0.088
	(0.418)	(0.097)	(0.802)	(1.052)
Lag CAR	−5.056	−0.285	8.567	−8.321
	(7.985)	(1.411)	(20.286)	(5.668)
Spread	0.375***	0.096***	0.399***	0.238***
	(0.134)	(0.037)	(0.142)	(0.067)
Spread × Log Assets	0.026		0.059**	
	(0.021)		(0.028)	
Spread × Lag CAR	−2.085***		−2.659***	
	(0.793)		(0.847)	
Bond Controls:				
Nominal Maturity	−0.021*	−0.007***	−0.026**	−0.017***
	(0.011)	(0.002)	(0.013)	(0.004)
WAL	0.027	−0.005	0.048	−0.014
	(0.031)	(0.006)	(0.046)	(0.017)
Log Bond Size	0.059	0.108***	0.031	0.267***
	(0.057)	(0.034)	(0.059)	(0.053)
Term Structure Level	−0.223	0.618***	−0.005	1.480***
	(0.266)	(0.179)	(0.483)	(0.186)
Term Structure Slope	0.266	0.417***	0.535	1.048***
	(0.322)	(0.122)	(0.574)	(0.243)
Asset Type & Issuance Year	Yes	Yes	Yes	Yes
Risk Weight Category RWC	Yes	Yes	Yes	Yes
Interactions & Fixed Effects:				
Bond Controls × Log Assets	Yes	Yes	Yes	Yes
Bond Controls × Lag CAR	Yes	Yes	Yes	Yes
Bank FE	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 4: **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 are: $Lag\ CAR$ = capital adequacy ratio lagged by one year-quarter; $Log\ Assets = Log(Bank\ Assets)$; *Spread* = bond yield spread; *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; RWC, issuance year, and asset type dummies. Interactions of bond controls and risk weight categories RWC with the variables *Log Assets* and *Lag CAR* are included. 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)
Log Assets	-108.873***	0.924***	-168.642***	-0.468
	(30.407)	(0.221)	(49.687)	(2.664)
Lag CAR	-350.479	-14.898*	241.822	-37.941**
	(549.487)	(7.880)	(1158.613)	(16.341)
Spread	22.456***	0.510***	21.557***	0.654***
	(8.323)	(0.141)	(8.260)	(0.176)
Spread x Log Assets	1.322		2.535*	
	(1.195)		(1.390)	
Spread x Lag CAR	-119.856***		-130.757***	
	(46.794)		(41.437)	
Risk Weight Category RWC	Yes	Yes	Yes	Yes
Bond Controls & Interactions	Yes	Yes	Yes	Yes
Bank Fixed Effects	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 5: **Risk weight bias & collateral quality.** 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. Panel A, Models V and VI both explore the role of *Risk Weight Bias* in bond purchase decisions. Panel B, Models VII and VIII explore how collateral risk as characterized by high collateral delinquency influences bond purchase decisions. Only Models VI and VIII control for bank fixed effects. The independent variables are: *Lag CAR* = capital adequacy ratio lagged by one year-quarter; *Log Assets* = Log(Bank Assets); *Delinquency* = bond collateral delinquency; *Risk Weight Bias* = measure of risk weight misclassification (see Appendix B.3). All models control for the bond characteristics *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; *RWC*, issuance year, and asset type dummies. Models VII and VIII include further controls *Subordination* = part of deal subordinated to bond standardized by collateral pool balance; *Dummy Guarantee* = 1 if bond is guaranteed; *No. of Tranches* = number of tranches in deal. Interactions of bond controls and risk weight categories *RWC* with the variables *Log Assets* and *Lag CAR* are included. 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).

Panel A: Risk Weight Bias	Model V		Model VI	
Dep. Variable: *Purchase Yes/No*	Coeff (1)	AME (2)	Coeff (3)	AME (4)
Log Assets	−1.799***	0.266***	−3.179***	0.076
	(0.394)	(0.096)	(0.787)	(1.048)
Lag CAR	−7.913	−0.251	5.422	−8.176
	(7.974)	(1.415)	(20.257)	(5.719)
Risk Weight Bias	0.573**	0.183***	0.611**	0.451***
	(0.232)	(0.061)	(0.242)	(0.098)
Risk Weight Bias × Log Assets	0.044		0.074	
	(0.042)		(0.055)	
Risk Weight Bias × Lag CAR	−2.906**		−3.376***	
	(1.306)		(1.283)	
Risk Weight Category RWC	Yes	Yes	Yes	Yes
Bond Controls & Interactions	Yes	Yes	Yes	Yes
Bank Fixed Effects	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
Panel B: Collateral Delinquency	**Model VII**		**Model VIII**	
Dep. Variable: *Purchase Yes/No*	Coeff (1)	AME (2)	Coeff (3)	AME (4)
Log Assets	−1.742***	0.190***	−7.379***	−0.816
	(0.539)	(0.074)	(1.249)	(0.728)
Lag CAR	19.572***	−0.119	129.713***	−13.189**
	(6.044)	(1.11)	(20.530)	(5.598)
Delinquency	−0.041	−0.027***	0.180	−0.110**
	(0.044)	(0.010)	(0.113)	(0.047)
Delinquency × Log Assets	0.009		0.033	
	(0.017)		(0.030)	
Delinquency × Lag CAR	−0.818**		−2.441**	
	(0.357)		(1.068)	
Risk Weight Category RWC	Yes	Yes	Yes	Yes
Bond Controls & Interactions	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	Yes
N Observations	81,135	81,135	27,289	27,289
N Banks	58	58	18	18
N Bonds	1,529	1,529	1,529	1,529
Pseudo R^2	0.312	0.312	0.398	0.398
Hosmer-Lemeshow GoF (p-val.)	0.646	0.646	0.975	0.975

Table 6: **Robustness to logit, complementary log-log, and linear probability models.** Reported are regression coefficients and average marginal effects (in percent) of logit and complementary Log-Log estimations as well as the marginal effects (in %) of two OLS specifications. The dependent variable is 1 if the bank purchases the bond and zero otherwise. The independent variables are: *Lag CAR* = capital adequacy ratio lagged by one year-quarter; *Log Assets* = *Log*(*Bank Assets*); *Spread* = bond yield spread; *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; *RWC*, issuance year, and asset type dummies. Interactions of bond controls and risk weight categories *RWC* with the variables *Log Assets* and *Lag CAR* are included. 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		OLS	
	Coeff	AME	Coeff	AME	ME	ME
Dep. Variable: *Purchase Yes/No*	(1)	(2)	(3)	(4)	(5)	(6)
Log Assets	−4.442***	0.282***	−4.338***	0.283**	−1.657**	−1.676**
	(1.177)	(0.111)	(1.171)	(0.112)	(0.666)	(0.662)
Lag CAR	−9.548	−0.139	−8.966	−0.123	−0.639	−1.246
	(21.507)	(1.453)	(21.181)	(1.455)	(5.994)	(6.845)
Spread	1.062***	0.087**	1.056***	0.085*	0.041	−0.093
	(0.355)	(0.043)	(0.349)	(0.044)	(0.046)	(0.061)
Spread × *Log Assets*	0.037		0.028		0.081**	0.085**
	(0.060)		(0.059)		(0.038)	(0.037)
Spread × *Lag CAR*	−5.637***		−5.511***		−0.504*	
	(1.989)		(1.938)		(0.271)	
Spread × (*Lag CAR* < *Q10*)						0.213*
						(0.124)
Spread × (*Q10* ≤ *Lag CAR* < *Q25*)						0.112
						(0.090)
Spread × (*Q25* ≤ *Lag CAR* < *Q50*)						0.101
						(0.122)
Risk Weight Category RWC	Yes	Yes	Yes	Yes	Yes	Yes
Bond Controls & Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	No	No	No
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
Pseudo R^2	0.229	0.229			0.012	0.0122
Hosmer-Lemeshow GoF (p-value)	0.540	0.540				

Appendix A

A.1 Proof of Proposition 1

To show that investment into x_2 relative to x_1 is higher for $\lambda > 0$, it suffices to check whether the derivative $\partial \left(\frac{x_2}{x_1+x_2} \right) / \partial\lambda$ is positive. This is indeed true for $\mu_S > 0$:

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

where the denominator is given as

$$\begin{aligned} Denom. = \Big\{ &- \left(\beta_2 \sigma^2_{\epsilon,1} + \beta_1 \sigma^2_{\epsilon,2} \right) \sigma^2_{\epsilon,3} \cdot \mu_S \; + \; \lambda \cdot \Big[\left(\sigma^2_{\epsilon,1} + \sigma^2_{\epsilon,2} \right) \sigma^2_{\epsilon,3} \cdot w_{low} \; + \\ &\sigma^2_S \cdot \Big(-\beta_3 \left(\beta_2 \sigma^2_{\epsilon,1} + \beta_1 \sigma^2_{\epsilon,2} \right) w_{high} + \left(\beta_3^2 \left(\sigma^2_{\epsilon,1} + \sigma^2_{\epsilon,2} \right) + (\beta_1 - \beta_2)^2 \sigma^2_{\epsilon,3} \right) w_{low} \Big) \Big] \Big\}^2 . \end{aligned} \tag{A.2}$$

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

A.2 Proof of Proposition 2

A bank with a binding regulatory constraint chooses a portfolio allocation with a different portfolio-beta β_{PF} than an unconstrained bank. The portfolio beta is defined as

$$\beta_{PF} = \frac{x_1\beta_1 + x_2\beta_2 + x_3\beta_3}{x_1 + x_2 + x_3} \; . \tag{A.3}$$

Its derivative with respect to λ is

$$\begin{aligned} \frac{\partial \beta_{PF}}{\partial \lambda} = &\underbrace{\frac{\mu_S \cdot \left[\left(\beta_1^2 \sigma^2_{\epsilon,2}\sigma^2_{\epsilon,3} + \beta_2^2 \sigma^2_{\epsilon,1}\sigma^2_{\epsilon,3} + \beta_3 \sigma^2_{\epsilon,1}\sigma^2_{\epsilon,2} \right) \sigma^2_S + \sigma^2_{\epsilon,1}\sigma^2_{\epsilon,2}\sigma^2_{\epsilon,3} \right]}{Denominator}}_{>0} \\ &\cdot \underbrace{\begin{aligned} \Big[&\left(\beta_3(\beta_3 - \beta_2)\sigma^2_{\epsilon,1} + \beta_3(\beta_3 - \beta_1)\sigma^2_{\epsilon,2} + (\beta_1 - \beta_2)^2 \sigma^2_{\epsilon,2} \right) \cdot w_{low} \\ &- \left(\beta_2(\beta_3 - \beta_2)\sigma^2_{\epsilon,1} + \beta_1(\beta_3 - \beta_1)\sigma^2_{\epsilon,2} \right) \cdot w_{high} \Big] \end{aligned}}_{\gtreqless 0} \end{aligned} \tag{A.4}$$

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

$$w_{high} > \frac{\beta_3(\beta_3 - \beta_2)\sigma^2_{\epsilon,1} + \beta_3(\beta_3 - \beta_1)\sigma^2_{\epsilon,2} + (\beta_1 - \beta_2)^2 \sigma^2_{\epsilon,2}}{\beta_2(\beta_3 - \beta_2)\sigma^2_{\epsilon,1} + \beta_1(\beta_3 - \beta_1)\sigma^2_{\epsilon,2}} \cdot w_{low} \; . \tag{A.5}$$

Note that the right hand side of Inequality (A.5) 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

$$\beta_3 < \frac{\beta_2^2 \sigma_{\epsilon,1}^2 + \beta_1^2 \sigma_{\epsilon,2}^2}{\beta_2 \sigma_{\epsilon,1}^2 + \beta_1 \sigma_{\epsilon,2}^2} < \beta_2 \ , \tag{A.6}$$

then a bank with a binding regulatory constraint chooses a higher portfolio-beta than an unconstrained bank. To see this, note that (A.6) implies that $\beta_2(\beta_3 - \beta_2)\sigma_{\epsilon,1}^2 + \beta_1(\beta_3 - \beta_1)\sigma_{\epsilon,2}^2$ in (A.4) is negative. It follow that derivative $\frac{\partial \beta_{PF}}{\partial \lambda}$ is now positive if Inequality (A.5) is satisfied. At the same time, (A.6) also implies that the right hand side of Inequality (A.5) is now smaller than w_{low}. As w_{high} must be larger than w_{low}, it follows that Inequality (A.5) is always satisfied and that $\frac{\partial \beta_{PF}}{\partial \lambda}$ is, hence, always positive provided Inequality (A.6) is true. If the regulatory constraint is binding and misclassification of securities 2 and 3 is as pronounced as in Inequality (A.6), 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 (A.6) is satisfied. To sum up, whenever (A.6) 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.

Appendix B

B.1 Risk taking *across* risk weight categories

I estimate the specification in Table 3, Model 1 again. However, this time I do not control for the risk weight categories *RWC* of bonds and, therefore, measure yield-seeking *across* risk weight categories. Table B.1, Columns (1) and (2) report the coefficient estimates and average marginal effects, respectively. The yield spread of a bond has an average marginal effect of 0.039% on the probability of security acquisition. It is not statistically significant and lower than in the baseline specification with *RWC* controls (Table 3).

Figure B.1 illustrates the interaction effects *Spread* × *Lag CAR* and *Spread* × *Log Assets* in a model without *RWC* controls. Graph (1) shows the average marginal effect of *Spread* at different values of *Lag CAR*. The convexity of the curve is much less pronounced than in the specification with *RWC* controls (Figure 3, Graph 1). Banks with tight regulatory constraints are less seeking higher yields *across* risk weight categories than they are reaching for yield *inside* risk weight categories. Similar conclusion can be drawn from an analysis of the interaction effect *Spread* × *Log Assets* in Figure B.1, Graph (2).

B.2 Estimation of the average yield spread and risk weight of ABS purchases

I estimate the yield spread and risk weight 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 3, 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

$$\widehat{AP}_i(c, y) = \Pr(\hat{\beta}\mathbf{X}_i | c, y) \tag{B.1}$$

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

$$\widehat{AAP}(c, y) = N^{-1} \sum_i \Pr(\hat{\beta}\mathbf{X}_i | c, y) \ . \tag{B.2}$$

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 B.3, 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

$$\omega(c, y) = \frac{\widehat{AAP}(c, y)}{\sum_{i \in \mathbf{Y}} \widehat{AAP}(c, i)} \ , \tag{B.3}$$

$$\text{for } \mathbf{Y} = \{16bps, 30bps, 35bps, 50bps, 60bps, 85bps, 115bps, 150bps, 220bps\}. \tag{B.4}$$

which are shown for a *Lag CAR* equal to 9% in Table B.3, 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 by a bank with *Lag CAR* equal to c:

$$\widehat{YS}(c) = \sum_{y \in \mathbf{Y}} \omega(c, y) \cdot y. \tag{B.5}$$

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 B.3, Panel A).[57] 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

$$\widehat{RWC}(c) = \sum_{r \in RWC} \omega(c, r) \cdot r. \tag{B.6}$$

[57] 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 B.4.

B.3 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}, $RWC_{AA+,AA,AA-}$, RWC_{A+}, ...) and a set of bond controls BC.[58]

$$YS = \beta_{RWC}\ RWC + \beta_{BC}\ BC + \varepsilon \tag{B.7}$$

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 category r is defined as the (corrected) yield spread in excess of the average spread implied by the next lower risk weight category $(r + 1)$.[59]

$$Risk\ Weight\ Bias = \max\{\widehat{YS}^{corrected} - \widehat{\beta}_{RWC}(r + 1), 0\} \tag{B.8}$$

The cut-off $\widehat{\beta}_{RWC}(r + 1)$ in Eq. (B.8) 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.

B.4 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 0.89% and has a standard deviation of 2.00%.

The sample of bonds with delinquency data is not a sub-sample of the bonds used in Section 6.1. 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. Thirty-nine percent of the sample with delinquency data are residential mortgage-backed securities, the rest are other asset-backed securities. Forty-nine percent of this sample is backed by collateral from the USA, 20% by Spanish, 11% by British, 9% by Dutch, and 4% by German collateral. Sixty-five percent of the securities carry a AAA and 11 % a $AA+$, AA or AA- rating.

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%.

[58] 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.

[59] *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 2, Panel C).

The subordination level is winsorized at the 1% level in each tail of its distribution. Five percent of the ABS benefit from some kind of guarantee. The average ABS belongs to a deal with five other tranches.

B.5 Robustness of investment volume regressions

In Table B.4, Columns (1) and (2), I estimate ordinary least squares regressions without and with bank fixed effects. I include dummies for risk weight categories RWC as well as the interactions $RWC \times$ *Lag CAR* and $RWC \times$ *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 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 B.4, Columns (3) to (8)). The robust interaction effect *Spread* × *Lag CAR* is illustrated in Figure B.2, Graph (1) without and Graph (2) with bank fixed effects.

B.6 Who buys the ABS with a high ratio yield spread over risk weight?

The model in Rochet (1992) predicts that banks with tight regulatory constraints shift investment to assets with a high ratio of *Yield Spread* over *Risk Weight*. In Table B.5 I test this prediction. I replace the variable *Yield Spread* and the controls for the risk weight categories *RWC* by the ratio *Spread/Risk Weight*. Otherwise the probit specifications are identical to Models I and II in Table 3.

The ratio *Spread/Risk Weight* has an average marginal effect of 1.720% on the probability that a bank buys a given ABS in Table X, Column (2). If bank fixed effects are included, the effect increases to 4.102%. In Figure B.2, Graphs (3) and (4) show the interaction effects *Spread/Risk Weight* × *Lag CAR* in both models with and without bank fixed effects. Clearly, banks with tight regulatory constraints (low CARs) are more likely to buy ABS that promise a relatively high yield spread relative to their risk weight.

B.7 Sub-sample analysis for ABS with different risk weights

I check the robustness of the results in Section 6 for the sub-sample of only AAA rated bonds with an IRB base risk weight of 12%. Otherwise, the specification is identical to Model I in Table 3. Figure B.2, Graph (5) shows the interaction effect of *Spread* × *Lag CAR*. The average marginal effect of *Spread* remains significant at the 5% level for *Lag CAR* values of 8, 9 and 10%. Once bank fixed effects are included (Figure B.2, Graph (6)), the average marginal effect of *Spread* at a *Lag CAR* of 8% increases to 1.095%. The convexity of Graph (2) indicates a strong interaction effect *Spread* × *Lag CAR* in the risk weight category for AAA rated ABS.

I also check if reaching for yield is more pronounced in some risk weight categories than in others. I use Model I from Table 3 (without bank fixed effects) to compute *RWC*-

specific estimates for the average marginal effect of *Spread*. Figure B.3, Graph (1) shows these *RWC*-specific estimates for banks with different *Lag CAR*. The graphs suggest that banks with tight regulatory constraints (low CARs) reach for yield only in risk weight categories with ratings from *AAA* to *A*. Similar observations can be made analyzing Figure B.3, Graph (2) which is estimated using Table 3, Model II with bank fixed effects. However, since several risk weight categories (in particular those with low ratings) have only a few bond observations, the *RWC*-specific estimates for reaching for yield are only measured with large error and should be interpreted with caution.

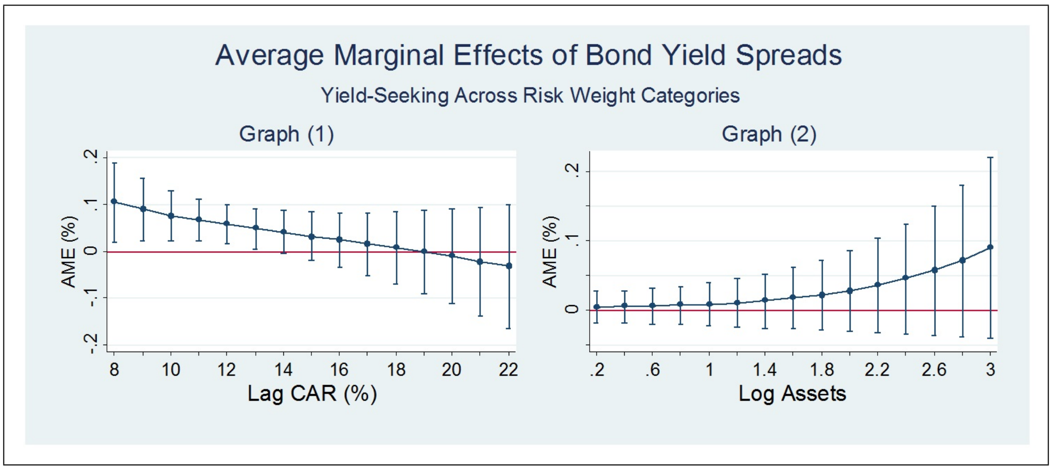

Figure B.1: Shown is the average marginal effect of the bond yield spread on the probability that a bank with given *Lag CAR* or *Log Assets* buys the ABS. The effects are estimated without controlling for risk weight categories *RWC*. Confidence intervals are drawn for the 5% level.

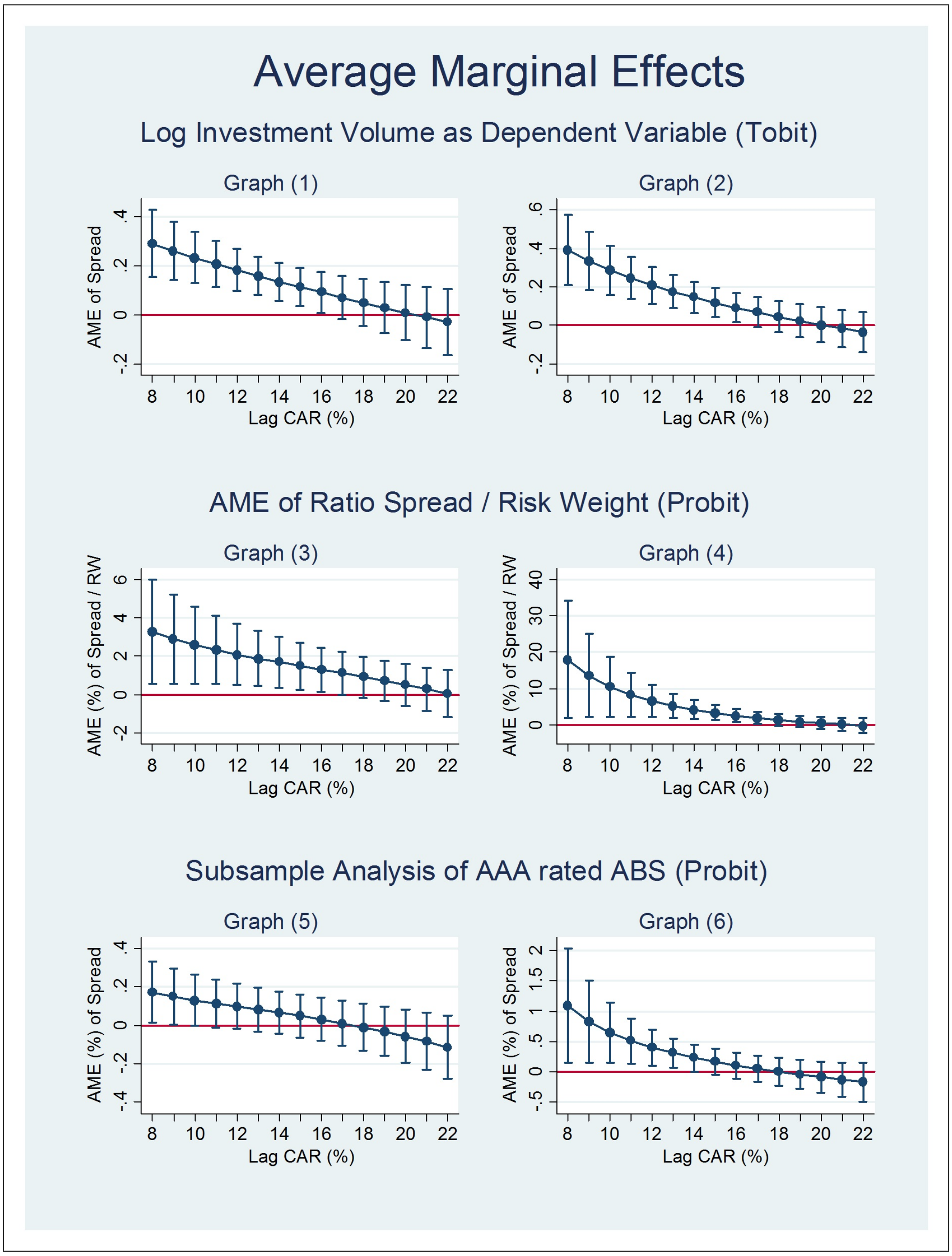

Figure B.2: Graphs (1) and (2) show the average marginal effect of the bond yield spread on the *Log Standardized Investment Volume* that a bank with given *Lag CAR* invests into the ABS. Graphs (3) and (4) show the average marginal effect of the ratio *Yield Spread / Risk Weight* on the probability that a bank with given *Lag CAR* buys the ABS. Graphs (5) and (6) 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. Only Graph (2), (4), and (6) control for bank fixed effects. Confidence intervals are drawn for the 5% level.

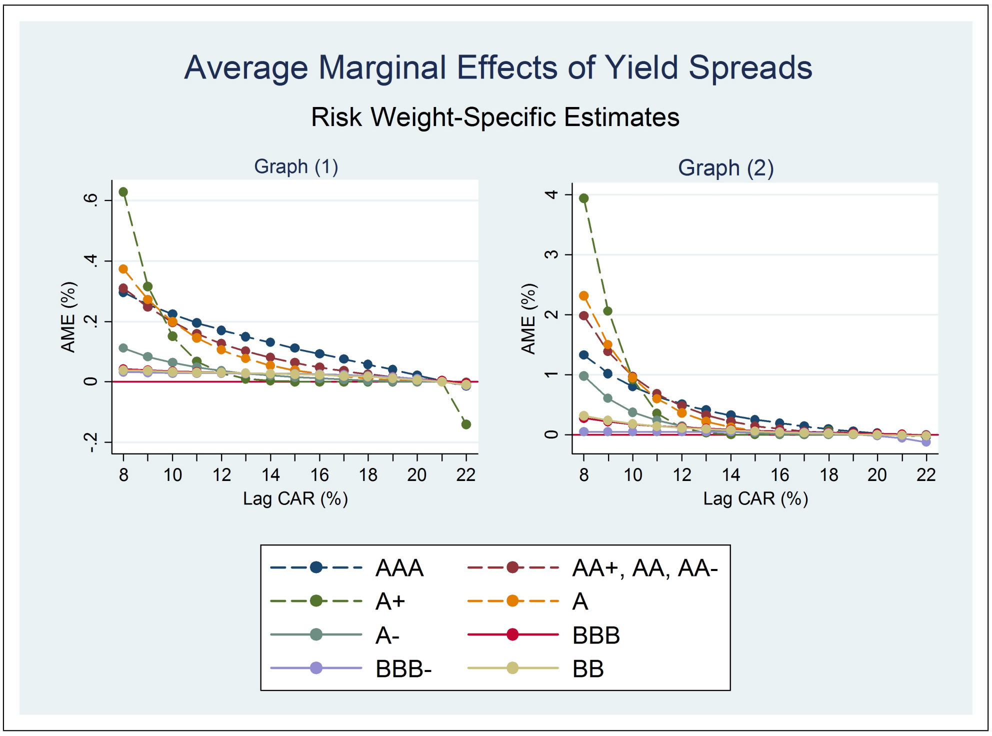

Figure B.3: The graph shows the *RWC*-specific estimates for reaching for yield. Average marginal effects of the yield spread are estimated for different values of *Lag CAR* and risk weight categories with different ratings. The estimates in Graph (1) are computed using Table 3, Model I without bank fixed effects. Graph (2) is estimated using Table 3, Model II with bank fixed effects.

Table B.1: **Yield-seeking across risk weight categories.** Reported are regression coefficients and average marginal effects (in %) of a probit estimation. The dependent variable is 1 if the bank purchases the bond and zero otherwise. The specification does not control for *RWC*. The independent variables are: *Lag CAR* = capital adequacy ratio lagged by one year-quarter; *Log Assets* = *Log*(*Bank Assets*); *Spread* = bond yield spread; *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; issuance year and asset type dummies. 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).

Dep. Variable: *Purchase Yes/No*	Coeff (1)	AME (2)
Log Assets	−1.867***	0.262***
	(0.454)	(0.095)
Lag CAR	−5.650	0.241
	(9.139)	(1.324)
Spread	0.211	0.039
	(0.142)	(0.028)
Spread × *Log Assets*	0.014	
	(0.020)	
Spread × *Lag CAR*	−1.309	
	(0.799)	
Bond Controls:		
Nominal Maturity	−0.022*	−0.008***
	(0.012)	(0.003)
WAL	0.027	−0.011*
	(0.032)	(0.007)
Log Bond Size	0.087	0.150***
	(0.087)	(0.037)
Term Structure Level	−0.215*	0.614***
	(0.256)	(0.176)
Term Structure Slope	0.208	0.379***
	(0.301)	(0.109)
Asset Type & Issuance Year	Yes	Yes
Risk Weight Category RWC	No	No
Interactions & Fixed Effects:		
Bond Controls × *Log Assets*	Yes	Yes
Bond Controls × *Lag CAR*	Yes	Yes
Bank FE	No	No
N Observations	102,239	102,239
N Banks	58	58
N Bonds	1,884	1,884
Pseudo R^2	0.218	0.218
Hosmer-Lemeshow GoF (p-value)	0.691	0.691

Table B.2: **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 3. 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*** (0.083)	-	0.2	0.015 (0.012)	0.020
9	0.190*** (0.063)	0.042	1.6	0.049* (0.026)	0.026
15	0.079*** (0.029)	0.028	2.8	0.183** (0.080)	0.040
20	0.017 (0.041)	0.019	3.0	0.227** (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*** (0.464)	-	0.2	0.088 (0.350)	0.386
9	0.902*** (0.315)	0.008	1.6	0.168 (0.182)	0.420
15	0.183*** (0.049)	0.007	2.8	0.239 (0.187)	0.428
20	0.021 (0.057)	0.004	3.0	0.254 (0.266)	-

Table B.3: **Predicted ABS yield spread and risk weight.** 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 3, 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	

Table B.4: **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 a Tobit specification. 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). The independent variables are: *Lag CAR* = capital adequacy ratio lagged by one year-quarter; *Log Assets* = *Log*(*Bank Assets*); *Spread* = bond yield spread; *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; *RWC*, issuance year, and asset type dummies. Interactions between bond controls and risk weight categories *RWC* with the variables *Log Assets* and *Lag CAR* are included. Standard errors are reported in parentheses and 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)
Log Assets	−0.139*	−0.183	-0.102**	-0.127***	-34.834***	0.248***	-53.188***	-0.157
	(0.083)	(0.133)	(0.039)	(0.047)	(7.315)	(0.058)	(12.406)	(0.663)
Lag CAR	0.216	0.186	-0.023	-0.049	-95.083	-3.994**	135.253	-9.586***
	(1.045)	(0.973)	(0.388)	(0.400)	(158.456)	(1.902)	(340.218)	(3.693)
Spread	0.032*	0.031*	0.004	0.004	7.245***	0.144***	6.778***	0.172***
	(0.018)	(0.018)	(0.004)	(0.004)	(2.612)	(0.040)	(2.395)	(0.044)
Spread x Log Assets	0.006	0.006	0.005**	0.005**	0.469		0.901**	
	(0.004)	(0.004)	(0.002)	(0.002)	(0.381)		(0.420)	
Spread x Lag CAR	−0.142*	−0.135*	-0.034*	-0.030	-39.351***		-53.188***	
	(0.081)	(0.080)	(0.019)	(0.019)	(14.967)		(12.406)	
Risk Weight Categ. RWC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls & Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	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
	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

Table B.5: **Purchasing ABS with a high ratio of spread over risk weight.** 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. The specifications do not control for the risk weights of ABS and the variable *Yield Spread* is replaced by the ratio *Spread / Risk Weight* = bond yield spread divided by bond risk weight. The other independent variables are: *Lag CAR* = capital adequacy ratio lagged by one year-quarter; *Log Assets* = *Log*(*Bank Assets*); *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; issuance year, and asset type dummies. Interactions between bond controls with the variables *Log Assets* and *Lag CAR* are included. Bank fixed effects are controlled for in columns (3) and (4). Standard errors are reported in parentheses and clustered by bank. The symbols *, **, and *** represent significance levels at 10%, 5%, and 1% respectively.

	Probit w/o bank FE		Probit with bank FE	
	Coeff	AME	Coeff	AME
Dep. Variable: *Purchase Yes/No*	(1)	(2)	(3)	(4)
Log Assets	-1.898***	0.261***	-3.204***	-0.057
	(0.471)	(0.094)	(0.822)	(1.088)
Lag CAR	-5.273	0.292	7.684	-7.148
	(9.303)	(1.336)	(22.163)	(5.887)
Spread / Risk Weight	6.125***	1.720**	6.205**	4.102***
	(2.326)	(0.736)	(2.482)	(1.457)
Spread / Risk Weight x Log Assets	0.361		1.067	
	(0.492)		(0.788)	
Spread / Risk Weight x Lag CAR	-31.705**		-42.388**	
	(12.430)		(16.825)	
Risk Weight Category RWC	No	No	No	No
Bond Controls & Interactions	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	Yes
N Obs	102239	102239	41988	41988
N Banks	58	58	23	23
No Bonds	1,884	1,884	1,884	1,884
R2	0.2178	0.2178	0.2637	0.2637