Complexity in Structured Finance*

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Abstract

We study complexity in the market for securitized products, a market in which it is easy for buyers to observe prices but difficult to observe product quality. We find that securities in more complex residential MBS deals default more and have lower IRRs. The higher likelihood of default is economically meaningful: a one standard deviation increase in complexity represents an 18% increase in default on AAA securities. However, yields of more complex securities are not higher indicating that investors do not perceive them as riskier. A channel by which complexity affects security default is the diversion of collateral cash from higher-rated to residual tranches.

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1. Introduction

Mortgage-backed securities (MBS) are created by the pooling and tranching of loans into multiple securities oftentimes with various credit enhancements. Their structures are detailed in lengthy prospectuses and prospectus supplements, many of them hundreds of pages long, describing the collateral, the allocation of cashflows from the pool of loans to the securities in various states of nature, the rating of the securities, and other structural features (e.g., collateral groups, subordination, and cross-collateralization). These non-standardized contingent contracts are traded in over-the-counter (OTC) markets, where investors buy and sell securities via intermediaries. While prices are relatively easy for investors in the MBS market to observe, the structure and quality of the product, i.e., the payoffs in various states of nature, are not. As prospective investors must carefully examine each security to understand the payoffs, increases in the complexity of securities raise buyers' search costs.[1]

There are two broad views of complexity in securitized products. If the goal of structuring is solely to create low-risk securities from collateral of variable quality (Gorton and Metrick (2013)), then complexity arises as a natural byproduct of structuring. The lower the quality of the collateral, the more elaborate and complex the structuring must be to create securities that have low default probabilities such as investors require for AAA-rated securities. Indeed, markets for sophisticated structured products have historically emerged as a way to disseminate high risk collateral.[2] Under this view, while complexity may be negatively correlated with the quality of the collateral (i.e., underlying loans in MBS products), there should not be a relation between the default of structured finance securities and complexity.

[1]There is a large literature in economics on search models. Rogerson, Shimer, and Wright (2005) and Lagos, Rocheteau, and Wright (forthcoming) survey the literature applying search models to labor and monetary economics. Recent contributions to search in the housing market include Piazzesi and Schneider (2009) and Ngai and Tenreyro (2014); Ngai and Tenreyro (2014) review earlier literature on housing search. Shimer and Smith (2000) and Smith (2006) provide search models of the marriage market. Duffie et al. (2005, 2007) build models of search and bargaining in OTC financial markets specifically.

[2]For example, the modern CMBS market developed to find investors for the assets of failed savings and loans (Jacobs, Manzi, and Fabozzi (2006)). Similarly, the collateral for the earliest Collateralized Debt Obligations (CDOs), which are particularly sophisticated structured securities, was high risk debt issued by corporations and governments in emerging market countries (Lucas, Goodman, Fabozzi, and Manning (2007), p. 4).

A less sanguine view is that issuers of securitized products use complexity for strategic reasons, thereby increasing the buyers' search costs and affecting the asset's quality-adjusted price. A recent line of research explicitly models the role of complexity in search models with homogeneous products, such as memory chips (Ellison (2005), Ellison and Ellison (2009), Ellison and Wolitzky (2012)). A related idea is that of Gabaix and Laibson (2006) wherein sellers shroud attributes of the product in a way that affects the true cost of the good after including "add-on" pricing. In these models, complexity is used to make it difficult to learn the quality-adjusted price of a good at the expense of buyers. These models focus on the difficulty of learning the price of a good of homogenous quality. In contrast, the MBS market is better characterized by prospective buyers who costlessly observe the price of a security but face search costs to learn the quality of goods with heterogeneous non-price characteristics.

In this paper, we ask how applicable the insights of these models of complexity are to OTC markets by examining the empirical relations between security complexity, security default, and yields.[3] We start by constructing six variables that proxy for the complexity of structured products. For each deal, we collect data on (i) the number of collateral groups and (ii) the number of securities (i.e., tranches). In addition, using the prospectus supplement of a deal, we count (iii) the number of pages specifically describing the collateral, (iv) the number of pages specifically describing the division of cashflows from the pool of loans to the securities, (v) the number of terms in the glossary of the prospectus supplement, and (vi) the file size of the prospectus supplement. These six variables are designed to measure the informational demands MBS deals impose on investors and the intricacies in structure across deals. While correlated, they capture different facets of the complexity of structured products. We also construct a summary measure of complexity – an index of complexity – that synthesizes the information available in our six individual variables. Since there are tradeoffs between using an index and the underlying economic variables, we use both in our empirical work.

[3] In addition to academic articles, the discussion of security complexity features prominently in the 2011 Financial Crisis Inquiry Commission's Report as a plausible contributing factor to the financial crisis.

We then use data from the private label MBS (PLMBS) market, a segment of the MBS market that includes most subprime MBS, together with our measures of complexity to establish the following facts. Controlling for the year the security is issued, securities of more complex deals default more *ex post* and are hence riskier. A one standard deviation increase in the complexity index is associated with a three percentage point increase in the risk of default. The relation between complexity and security performance is particularly strong for securities rated AAA at issuance. For these securities, a one standard deviation increase in complexity is associated with a 7.7 percentage point higher likelihood of default which is economically meaningful as it represents an 18% increase relative to the mean default level on AAA securities.[4] The finding is robust across a variety of specifications including controls for the lead underwriter of the deal. Following Chernenko (forthcoming), we also measure the IRRs on the securities and find that the IRRs are lower for more complex securities.

Our default results do not solely reflect issuers masking low quality collateral with complexity. We arrive at this conclusion for two reasons. First, we find that the relation between complexity and collateral performance (i.e., the performance of the underlying loans) is less robust than the one between complexity and security performance. More importantly, controlling for collateral performance directly in our regressions does not substantially alter the magnitude of the relation between complexity and security default.

Rather, we find evidence that one channel by which complexity may affect security default is by facilitating the diversion of collateral cash to lower-rated tranches, to the disadvantage of senior tranches, when the collateral is performing well. We find that the residual tranches are more likely to have received cash flows when the deal is more complex. This left the senior tranches with less protection when the adverse home price scenario occurred such that more of them defaulted. Because issuers usually own the residual tranches (see, for example, Demiroglu and James (2012) and Begley and Purnanandam (forthcoming)), they benefit from the diversion.

[4]The mean default rate in our AAA subsample is 42 percentage points. A 7.7 percentage point increase in the likelihood of default therefore represents an 18% (7.7/42) higher likelihood of default.

The finding that securities in more complex deals default more is not, in and of itself, evidence that complexity disadvantages investors. If investors receive higher spreads in exchange for assuming the higher default risks, complexity may simply be a good proxy for credit risk. However, we find that securities of more complex deals have *lower* spreads at issuance indicating that, *ex ante*, investors did not perceive them as riskier. This result is intriguing because, in light of the higher default rates of complex deals, we would anticipate observing higher, rather than lower, spreads as compensation for additional credit risk.

The findings that more complex securities default more and that this greater default risk is not priced, indicate that large institutional investors, who are the primary participants in the MBS market, do not fully process the information in elaborate securities. As such, they do not demand a risk premium to hold more complex securities that will default more often. Issuers, aware of the limitations of market participants, can use complexity to price low quality securities at par with high quality securities. In other words, it literally pays issuers to be complex. If, alternatively, investors fully process information about the securities, issuers would either have to accept a lower price for more complex securities or would not be able to sell them at all.

Our findings are important for understanding the boom and bust in subprime securities. The majority of these securities defaulted, including more than 40% of securities rated AAA at issuance. Why did investors pour so much money into assets that ultimately proved so disastrous? One explanation is that they underestimated, or neglected entirely (Gennaioli, Shleifer, and Vishny (2012)), the possibility of a widespread decline in home prices. Indeed, subprime executives themselves did not expect that home prices would fall substantially (Cheng, Raina, and Xiong (2014)).[5] Such beliefs likely decreased investors' willingness to pay the search costs to fully understand the structure of these securities. Our results indicate that, furthermore, the complxity of subprime securities made it difficult for investors to understand exactly what they were buying. Our findings also help to explain the collapse

[5]Consistent with the findings of Cheng, Raina, and Xiong (2014), Gerardi, Lehnert, Sherlund, and Willen (2008) provide narrative evidence that many market participants viewed a significant fall in home prices as highly unlikely.

in trading of PLMBS during the crisis (see Gorton and Metrick (2012)) as they provide evidence of asymmetric information between different types of investors in the MBS market. Theoretical literature (e.g., Bhattacharya, Reny, and Spiegel (1995), Rahi (1996), Hanson and Sunderam (2013)) show that such asymmetric information can cause trading to collapse.

Finally, the failure of spreads to reflect the greater risks associated with complexity indicates that there may be welfare benefits from standardizing securitized products in the sense of Gale (1992). Such standardization may be particularly important if Fannie Mae and Freddie Mac play less of a role in the mortgage market going forward. Securities issued by the GSEs (agency MBS) are quite simple by our measures: their offering circulars are short, there are few securities within a deal, and they usually only have one collateral group.[6]

Our paper is related to a small but growing literature on security complexity. Carlin, Kogan, and Lowery (2013) look at the effect of complexity on trading in a laboratory setting. Célérier and Vallée (forthcoming) study complexity in the market for French retail structured products. Furfine (2014) finds that *loans* in more complex commercial MBS (CMBS) deals default more and concludes from this that issuers used complexity to distract investors from the low quality collateral in the deals. Without further evidence, a finding that high risk collateral goes into more complex deals is entirely consistent with the efficient view of complexity in which issuers use it to create high quality securities from lower quality collateral.

Sato (2014) provides a theoretical model of the related concept of opacity. His model features two types of opacity, the second of which - an inability to observe asset payoffs - corresponds most closely to our notion of complexity. In the PLMBS market, investors could have understood the asset's payoff structure but they had to wade through a lot of information to do so. In the Sato model, investors observe the payoffs from a fund but not the payoffs of the individual assets held by the fund. The actual asset payoffs do not depend on opacity. Using this setup, Sato finds that opaque assets trade at a premium. In our empirical work, we find that more complex assets have lower payoffs (IRRs) but do

[6]Although agency MBS investors do not face default risk, they face substantial prepayment risk and, as such, there is still scope for structuring.

not offer higher spreads. Our results are thus consistent with the asset having a higher quality-adjusted price since the quality of the assets is lower.

The remainder of the paper proceeds as follows. In the next section, we describe the structure of the US MBS market and our measures of complexity. In Section 3, we describe our dataset and the complexity we observe in the MBS market. Section 4 documents how complexity relates to security performance. We explore the mechanism through which complexity is related to security performance in Section 5. In Section 6, we test whether investors understand that more complex deals are more likely to underperform. In Section 7, we discuss our results in the context of theories of security design and explore heterogeneity in complexity across issuers. Section 8 concludes.

2. The Structure of MBS and Measuring Complexity

The US residential MBS market can be divided into two main asset classes: 1) residential MBS issued by the GSEs or that use securities issued by the GSEs as collateral, and 2) residential MBS issued by non-government entities that are backed by mortgages or securities not guaranteed by the GSEs. The first market is commonly known as the agency market while the second is usually referred to as the PLMBS market. In this paper we focus exclusively on the PLMBS market as agency securities are simpler to understand and did not see nearly the same amount of distress as the PLMBS market during the 2007-2009 crisis and its aftermath. Within the PLMBS market, we confine our attention to an asset class known as home equity ABS. Market participants use this term to refer to securities backed by residential mortgage loans including first lien loans, home equity loans, and home equity lines of credit. Securities from the typical home equity ABS deal are marketed to investors as subprime (e.g., “RES B/C”) or Alt-A.

Institutions are the dominant investors in this market. While detailed data on holdings are not available for all investors, data from Table 2 of Chernenko, Hanson, and Sunderam (2014) indicate that insurers (life insurers and property and casualty combined) account for 8.3% of holdings over the 2003-2007 period while mutual funds account for another 1.2%.

Ghent, Hernández-Murillo, and Owyang (2015) estimate that the GSEs accounted for about 25% of the purchases of senior tranches while Adelino, Frame, and Gerardi (forthcoming) put the same share at 30%.

The securities are extremely illiquid: Bessembinder, Maxwell, and Venkataraman (2013) find that only about one fifth of non-agency structured finance securities trade in the 21 month period beginning in May 2011. The issuers and underwriters of ABS are usually large investment banks. For instance, in 2006, the peak of the ABS market, the largest three lead deal managers by issuance value were Lehman Brothers, RBS Greenwich Capital, and Goldman Sachs.

A typical ABS deal has many securities in it with a prioritization of cashflows from the underlying collateral to the top tranche (i.e., security) first, then to the second tranche, and so forth. In contrast, losses on the underlying collateral are typically applied to the lowest tranche first, then the next lowest, and so forth. Most securities within a deal are rated by multiple credit rating agencies (CRAs). The lowest tranches are usually unrated and are commonly referred to as the residual or equity piece since they behave much like equity in a firm.

Some ABS securities are used as collateral for Collateralized Debt Obligations (CDOs). As Coval, Jurek, and Stafford (2009) argue, CDOs are even more complex than ABS. The typical ABS-backed CDO usually consists of either investment grade ABS securities or mezzanine (e.g., BB or residual) ABS securities. We do not include CDOs backed by ABS in our dataset for three reasons. First, CDOs backed by residential MBS are a much smaller asset class than ABS. Second, getting data on these securities is far more challenging than gathering data on ABS. Bloomberg rarely has cashflows for CDOs backed by residential MBS and even less frequently has prospectus supplements for these deals. Finally, as we show, there is more than enough complexity in ABS for us to understand, explain, and exploit.

ABS deals often subdivide the overall loan pool backing a deal into multiple loan groups. In a typical deal structure, a loan group primarily supports a series of senior securities but potentially with cross-collateralization from other loan groups within the same deal. For example, the issuer divides the loans in deal ABC into loan groups 1 and 2. The loans in group 1 collateralize securities AAA-1, AA-1, and A-1. Group 2 collateralizes securities AAA-2, AA-2, and A-2. If the deal has a cross-collateralization provision, in the event securities AAA-1, AA-1, and A-1 are at serious risk of default due to poor performance of the loans in group 1, cash flows from group 2 loans could be diverted to securities AAA-1, AA-1, A-1 provided that the securities group 2 collateralizes (AAA-2, AA-2, and A-2) are at little risk of default or the prepayment rate on group 2 is such that, for example, AAA-2 has been entirely paid off. Regardless of whether a multiple loan group deal has cross-collateralization, more junior tranches within the deal are typically supported by the entire loan pool (i.e., all loan groups).

2.1. **Measuring Complexity.** We measure complexity at the deal level. The idea is to proxy for the heterogeneity in the structure of a securitization and the amount of information investors need to process in order to trade these assets. While the complexity of the collateral is not entirely distinct from the structure of the deal, our complexity measures primarily capture the complexity of the structure.

For a given deal, we define the following variables: (i) the number of collateral groups (*nloangroups*); (ii) the number of securities or tranches (*ntranches*); (iii) the number of pages in the prospectus supplement specifically describing the collateral (*pagesmpool*); (iv) the number of pages in the prospectus supplement specifically describing the division of cashflows from the collateral to the securities in the deal (i.e., the waterfall) and details of the securities more generally (*pageswaterfall*); (v) the number of terms in the glossary (*nglossaryterms*); and (vi) the file size of the prospectus supplement (*filesizemb*). All six variables are observable at issuance of the security.

A larger number of collateral groups makes the deal more complex because it allows for more complex waterfall structures. A larger number of tranches also permits a more complex rule for allocating the cashflows from the collateral to the securities as well as more state-contingent clauses. A well-informed investor would need more time to understand what cashflows he or she would recieve in various states of the world as either of these variables increase.

The portions of the prospectus supplement we use to define *pagesmpool* are the part of the supplement under the heading "Description of the Mortgage Pool" or a similar heading and any annex, schedule, or appendix that has tables detailing the characteristics of the loans. Some deals include tables of statistics detailing the mortgages directly in the section of the prospectus supplement labeled "Description of the Mortgage Pool" while others include these tables in an annex, schedule, or appendix. There are often separate tables for each loan group such that more loan groups implies a higher level of *pagesmpool*.

The portion of the prospectus supplement we use to define *pageswaterfall* is the part of the supplement under the heading "Description of the Certificates" or "Description of the Securities". Included in the waterfall are, for example, calculation of the principal and interest overcollateralization triggers and precise details regarding the mechanics of cross-collateralization. In defining *pagesmpool* and *pageswaterfall*, we do not include subsections of the section at the beginning of the supplement section typically headed "Summary" even if they include descriptions of the collateral or the waterfall as these subsections are less clearly demarcated than the main sections of the prospectus supplement.

We manually count the number of terms in the glossary of each prospectus supplement. Given the lack of standardization in the PLMBS market, sometimes this section of the prospectus supplment is instead called "Index of Terms" or "Index of Defined Terms". Having more terms to understand makes a deal more complex because, to understand what cash flows an investor will receive, he or she needs to understand more terms.

Finally, we include the file size of the prospectus supplement following the finding of Loughran and McDonald (2014) that the file size of a company's 10K is a good proxy for its readability.

2.2. **A Complexity Index.** While our complexity variables are correlated with one another, each one captures a different dimension of complexity. We thus construct an index of complexity, denoted by *complexityindex*, by extracting the first principal component across our six complexity variables at each point in time. The higher the index of complexity is, the greater the complexity of a deal. Measuring complexity using an index is convenient because we can include in our estimation information contained in all six variables jointly without facing the issue of collinearity. The drawback of using an index is that we lose the ease of economic interpretation. In the empirical analysis, we present results using the underlying complexity variables as well as the complexity index.

3. Data

We collected information on all PLMBS deals available on Bloomberg. Our sample starts in 2002 and ends in 2007 as the ABS market was quite small until the 2000s and there was very little issuance of ABS from 2008 onwards.[7] Issuance in our sample peaks in 2006 at more than half a trillion USD and, in 2007, is less than half of what it is in 2006 both in terms of dollar volume and number of deals. Issuance is less than \$100B in every year before 2002.

We restrict our attention to USD-denominated ABS backed by US assets for which Bloomberg has information on cashflows since the data quality is much higher for these securities. Our sample includes roughly half the ABS deals on Bloomberg. We manually collected all relevant information on our securities available from Bloomberg, including the prospectus supplement if it was available. Most our variables are measured at the time the deal was issued except for security default and the foreclosure rate on the collateral group. Security default is a binary variable that takes a value of 1 if the security had defaulted by August 2013. The foreclosure rate on the loan group is also measured in August 2013. We also collect data on the cashflows to the underlying security in each month from issuance to October 2016.

Our data contains variables that vary by deal, by security, and by collateral group. Most of our analysis is at the security level; we cluster our standard errors at the deal level as security performance should be correlated within a deal. We include securities rated BBB through

[7]Although there are a few ABS deals available on Bloomberg in the 1990s, we begin our sample in 2002 so that we can adequately control for heterogeneity in the year of issuance.

AAA in our security-level regressions and control for ratings using the ratings categories AAA, AA, A, and BBB.

Most securities issued are adjustable rate and, following Ashcraft, Goldsmith-Pinkham, Hull, and Vickery (2011), we drop fixed rate securities to focus on credit risk rather than prepayment risk. Our results are qualitatively the same when we include fixed rate securities in our sample. We also drop any securities collateralized by loan pools that include some fixed rate loans or for which the share of fixed rate loans in the collateral is unknown since deals with substantial fixed rate collateral may have even more complex structuring to mitigate prepayment risk.

The appendix contains additional details on our data set and the control variables.

3.1. **Complexity Variables.** Panel A of Table 1 summarizes our complexity variables. Although the modal deal has 2 loan groups, 13% of deals have 3 or more loan groups. The largest number of loan groups in a deal is the 11 groups in BSABS 2007-SD1. The average number of securities per deal is 18 and one deal, LXS 2007-3, contains 68 separate securities. The average prospectus supplement takes 38 pages to describe the collateral and 27 pages pages to describe the waterfall. The average number of terms in the glossary is 144 and the average file size is 1.4 megabytes with the largest file size being 34 megabytes.

The complexity index is normalized to have a standard deviation of one for ease of interpretation. To make it easier to see the time series pattern, we normalize *complexityindex* to have a mean of 0 in 2002 by subtracting the mean of *complexityindex* in 2002.[8] The factor loadings on the individual complexity variables in the index are 30% *nloangroups*, 28% *ntranches*, 16% *pagesmpool*, 13% *pageswaterfall*, 11% *nglossaryterms*, and 1% *filesizemb*.

Panel B of Table 1 describes the variation in *complexityindex* within each year in our sample. Investors in a given year faced substantial heterogeneity in the complexity of deals. At the deal-level, the standard deviation of *complexityindex* across all years is 0.96 while it is 1.11 for 2007 deals, 0.91 for 2005 deals, and 0.86 for 2003 deals.

[8]The normalization is done at the security level as this is the unit of observation for our analysis, rather than at the deal level for which we show results in Table 2 and summary statistics in Table 1. Because of this, the standard deviation in Table 1 is not exactly one and the level in 2002 in Figure 1 is not exactly 0.

As Figure 1 illustrates, complexity increases over time. For example, in 2002 the average number of securities in a deal is 11 but, by 2007, it almost doubles to 19. Over our sample period, *pagesmpool*, *pageswaterfall*, *nglossaryterms*, and *filesizemb* all grow steadily. Deal size also increases over our sample. The number of loan groups in each deal is roughly stable over time.

While we document increases in complexity over the sample period, we do not interpret increased complexity as evidence of substantial financial innovation in securitization over the 2000s. We have no evidence that any of the features of ABS deals that increase their complexity were invented or even diffused during the 2000s. Markets for structured MBS had existed for a long time before the subprime boom. For example, Riddiough and Thompson (2011) document the existence of sophisticated MBS in the US since at least the 1850s.

As Table 2 shows, the complexity variables are correlated. The highest correlation (51%) between our complexity measures is between *nloangroups* and *ntranches*. The size of the prospectus supplement file is the complexity variable least correlated with the other complexity variables.

3.2. **Security Performance.** We define default to be an event in which the security has suffered a principal loss or in which one of the ratings agencies indicates the security is in default. For Moody's, this is a rating of Caa1 or lower. For S&P, this is a rating of CCC+ or lower while for Fitch this is a rating of CCC or lower. Default on a security is any loss such that defaults occur for most securities in our sample despite a loan group-level foreclosure rate of 15%.

We also calculate a finer-level of security performance using the cashflows to each individual tranche when the cashflows are available. We follow Chernenko (forthcoming) in calculating the IRR. To calculate the IRR, we assume the security was bought at par and that any outstanding principal balance not paid off by summer 2016 is paid off in full on that date. The cashflows for the months in between are the actual cashflows received by the security. We do not calculate the IRRs for securities with negative interim cashflows, that are interest only, that are principal only, as well as those with very large outliers in a given cashflow. We winsorize the IRR at the 1% level to deal with several outliers; our results are quite similar when we winsorize at the 2% or 5% levels.

Table 3 describes our security-level performance variables. Overall, by August 2013, 74% of the securities in our sample had defaulted, including 42% of those rated AAA at issuance. By comparison, 84% of securities that had AA ratings at issuance had defaulted while 97% of securities originally rated A or BBB were in default.

The median AAA, AA, and security has a positive IRR. The bottom 10% of AAA securities clearly experienced losses since the IRR is negative for the bottom decile. Similarly, the bottom 25% of AA, A, and BBB securities have very negative IRRs indicating substantial losses. Across all ratings, however, the top 25% of securities have positive IRRs indicating minimal if any losses.

4. Security Performance and Complexity

We define $D_{i,t+T}$ as equal to one if security i issued at t has defaulted in our sample period, and zero otherwise. We model the probability of default using a probit,

$$P\left(D_{i,t+T}=1\right)=\Phi\left(Complex'_{i,j,t}\beta_1+Controls'_{i,j,t}\beta_2\right), \tag{1}$$

where $\Phi()$ is the cumulative standard normal distribution and $Complex_{i,j,t}$ is a vector of complexity variables for security i in deal j known at issuance of the security. A set of control variables, collected in the vector $Controls_{i,j,t}$, is observable at issuance of security i. The benchmark set of controls includes the deal size (*dealsize*), an indicator for cross-collateralization in the deal (*crosscollat*), the amount of excess spread in the deal (*excessspread*), the issuance volume of the lead manager in the year the deal was issued (*leadtot*), dummies for the year of issuance, controls for the geography of the collateral, dummies for the rating categories, the percentage subordination of the security (*subordination*), the spread above one month LIBOR the security promises (*spread*), and a dummy variable indicating whether the CRAs disagreed on the security's rating at issuance (*disagreetranche*). We include *disagreetranche* to capture the possibility that, for example, some investors treat what we code an AA security as an A security.

Table 4 contains the results from estimating equation (1). The table presents marginal effects from the probit estimates to facilitate understanding the economic magnitudes. As Columns 1 through 6 illustrate, all of our measures of complexity predict security default. The effects are statistically significant at the 1% level for five of our measures and statistically significant at the 5% level for *filesizemb*.

The effect of complexity on default is also economically important. The addition of one loan group increases the likelihood that a security will default by 3 percentage points. An increase of one standard deviation in the number of securities in a deal (5 securities) raises the likelihood that a security will default by 1.3 percentage points. An increase of 18 pages in the description of the collateral raises the chance of default by 1.2 percentage points. A one standard deviation (9 page) increase in the length of the waterfall description is associated with a 0.9 percentage point higher risk of default. A glossary with 72 additional terms is associated with a 2.2 percentage point increase in default while a one standard deviation increase in the size of the prospectus file is associated with a 1.2 percentage point higher rate of default.

Columns 7 and 8 of Table 4 present the effects of complexity when we combine our complexity variables. In Column 7, we include all 6 measures of complexity simultaneously without regard to potential collinearity. Although the magnitudes of the effects decrease, not surprisingly, *nloangroups*, *nglossaryterms*, and *filesizemb* continue to be statistically significant predictors of default at the 1% level while *pagesmpool* is statistically significant at the 10% level. In Column 8, we present our results from combining all complexity variables using their first principal component, *complexityindex*. The standard deviation of *complexityindex* is 1 and the interpretation of its marginal effect is that a one standard deviation increase in the overall complexity of the deal raises the risk of default by 3.5 percentage points.

Not surprisingly, AAA securities default the least and AA securities default the second least. Securities initially rated A do not default statistically less frequently than BBB securities. However, several variables beyond ratings predict default. Importantly, spreads on individual securities are highly predictive of default even after controlling for their rating, implying that investors priced securities using information beyond the rating. A 100 basis point increase in the spread is associated with a three percentage point greater risk of default.

We also see that more credit support in the form of subordination reduces the risk of default. A one percentage point increase in the level of subordination decreases the risk of default by approximately 0.7 percentage points. Larger deals also default more often.

4.1. **Realized Rates of Return and Complexity.** Our main measure of performance, default, is coarse and somewhat relies on the CRAs. We therefore also test whether more complex securities perform worse as measured by their IRRs. Table 5 shows the result of regressing the security's IRR on our individual complexity variables. The coefficients on all the complexity variables are negative indicating that the relation is negative; the relation is statistically significant for all measures except *filesizemb*. The magnitude is such that a one standard deviation increase in complexity is associated with a 2.3 percentage point lower IRR. This magnitude is more than the difference in moving from the median to the 75th percentile of the distribution of the IRR as illustrated by the summary statistics in Table 3.

4.2. **Security Performance Controlling for Collateral Performance.** In Table 6, we control for the performance of the collateral. In Column 2 of Table 6, we estimate equation (1) including *foreclosurerate* as a control variable while Column 3 controls for *collatlossshare*. Unsurprisingly, the coefficients on *foreclosurerate* and *collatlossshare* are positive and highly statistically significant.

What is more notable is that controlling for the *ex post* collateral quality only slightly reduces the strength the relation between *complexityindex* and security default. The marginal effect of a one unit increase in complexity falls from 3.6 percentage points (Column 1) to 3.3 and 3.1 percentage points in the specifications in which we do not control for collateral characteristics measured at issuance (Columns 2 and 3). The marginal effect falls from 2.8

percentage points to 2.6 and 1.9 percentage points when we use only the observations for which we can control for detailed collateral characteristics (Columns 5 and 6 of Table 6). As such, the main channel through which complexity relates to security performance is not the collateral.

4.3. **AAA Securities and Default.** As Table 7 shows, the relation between default and complexity is stronger for AAA securities than for all securities. For AAA securities, adding an additional loan group to a deal is associated with a 6.6 percentage point increase in the likelihood of default rather than the 2.7 percentage point increase we observed in our benchmark model. Issuing one more security in a deal results in a 40 basis point increase in the risk of default for AAA securities while for all securities the increase in the chance of default from one more security is only 26 basis points. We also see larger increases in the risk of default from increases in *pagesmpool*, *pageswaterfall*, *nglossaryterms*, and *filesizemb* for AAA securities.

Not only are the absolute magnitudes larger for AAA securities, the percentage increases in default are larger. More than 85% of securities rated below AAA default while only 42% of AAA securities default so that a given percentage point increase in the risk of default is a much larger percent change for AAA securities. As Column 8 shows, a one unit increase in *complexityindex* raises the likelihood of default by 7.7 percentage points for securities initially rated AAA which represents an 18% increase.

Furthermore, Table 7 shows that even AAA investors priced riskier securities higher as the spreads predict default. Our finding that spreads predict default for the *AAA* tranches, as well as lower-rated tranches, differs from that of Adelino (2009). Given that Adelino's security performance data is as of 2008Q3, the full effects of the housing crisis might not have been felt. Since we measure default much later (summer 2013), our measure of default may correspond better with the actual losses suffered by investors rather than forecasts of investment performance based on projections of how the housing crisis may or may not unfold.

4.4. **Sensitivity Analysis.** We conduct several sensitivity analyses of our results to our model specification. Table 8 presents the key alternative specifications using the summary variable *complexityindex*; the full results for the individual complexity variables are available from the authors upon request. Column 1 of Table 8 reproduces our benchmark specification with *complexityindex* (Column 8 of Table 4).

Columns 3 of Table 8 shows that, although complexity is a stronger predictor of default for AAA securities, it is also an economically important predictor of default for securities not rated AAA but the effect is not statistically significant. For securities not rated AAA, a one standard deviation increase in complexity is associated with a 1 percentage point rise in the likelihood of default. We also estimate the effect of complexity on securities in each rating category separately (results not shown) and found that the relation between complexity and default is similar for AA, A, and BBB securities.

In Column 4, we present the results from estimating equation (1) when we include additional summary characteristics about the loans as control variables. The specification in Column 4 adds the weighted average LTV at origination (*ltv*), the average FICO score on the loans (*fico*), the share of loans that are no or low documentation (*lownodocshare*), the share of loans with balances under $300,000, the share of loans with balances of $300,000 to $600,000, and the weighted average maturity (*wam*) of the loans to the vector of controls. All of these variables are available for only about half the securities and, as such, the specification in Column 4 cuts our sample in half. The coefficient on *complexityindex* continues to be statistically significant at the 1% level although its magnitude falls by about a sixth.

Column 5 contains the results from estimating equation (1) excluding securities collateralized primarily by pools of entirely conforming pools, i.e., those pools for which *conforming*=1. Our motivation for the specification in Column 5 is that the GSEs had a substantial demand for PLMBS and usually only purchased securities based on conforming pools (see Ghent, Hernández-Murillo, and Owyang (2015) and Adelino, Frame, and Gerardi (forthcoming)). Deals in which the GSEs bought a security might thus have almost mechanically had one more loan group which might in turn have increased measured complexity along other dimensions. One concern then is that our complexity variables are only picking up the influence of the GSEs. However, our results are quite similar when we exclude securities collateralized primarily by pools that the collateral group description describes as conforming.

In Column 6, rather than controlling for the size of the lead underwriter, we include fixed effects for the top 15 lead underwriters by issuance. The results are similar when we include deals from the top 10 or the top 20 underwriters. The results show that deals from the same underwriter that are more complex default more even after controlling for the year of issuance. The same underwriter varies the level of complexity in the deal, perhaps depending on the investors, and such variation in complexity is related to subsequent security performance. Thus, it does not appear that the relationship between complexity and security performance is because bad underwriters consistently use more complexity than good underwriters.

In Column 7, we include dummies for the quarter of issuance rather than the year of issuance to control for the possibility that there is time variation within year in security quality. We include only data from 2004-2007 in this set of results as there is too little issuance in some quarters in the early years of the sample.

In Column 8, we estimate a linear probability model. The coefficient on *complexityindex* continues to be highly statistically significant in the OLS estimate and the magnitude from the OLS estimate indicates a one standard deviation increase in complexity is associated with a 2.6 percentage point increase in the likelihood of default. The OLS estimate is slightly lower than the magnitude we get from our benchmark probit specification.

In another sensitivity exercise, we consider whether the results are sensitive to our way of controlling for the geography of the loan group. In particular, we estimate a specification in which, rather than controlling for the top 5 state shares, we control for the geographic concentration of the loan group. We measure the concentration of the loan group using a Herfindahl-Hirschmann Index (HHI) of the top five states in each loan group. The coefficients on our complexity variables are very similar to those in our other specifications. The results are available from the authors upon request.

Finally, we conduct our analysis using discrete measures of complexity to ensure the robustness of our results to outliers. For example, rather than including the number of loan groups itself as in Column 1 of Table 4, we include two dummy variables for the number of loan groups, *nloangroups2* and *nloangroups3ormore*. Similarly, rather than using the number of tranches as in Column 2 of Table 4, we include a dummy variable that takes a value of 1 if the number of securities in the deal was above the median and 0 otherwise. We construct parallel discrete measures of complexity for the number of pages in the prospectus supplement, the number of pages required to describe the collateral, the number of pages required to describe the waterfall, and the number of disagreements in the deal. The results from using these discretized complexity measures also imply that the risk that a security will default increases with its complexity. The results using discretized complexity measures are available from the authors upon request.

5. Understanding the Mechanism

We have established that complex securities default more. There are at least two reasons, which are not mutually exclusive, for this relation. First, issuers may use complexity to mask collateral that is lower in quality in ways that investors cannot easily observe. Although investors can easily observe key summary characteristics of the collateral (e.g., the average LTV of the loans in the deal), issuers may still have better information about the quality of the collateral. If this is the case, we would expect to observe a higher foreclosure rate or overall loss rate on the collateral *ex post*.

In Table 9, we regress either the foreclosure or collateral loss rate of the loan group on all observable collateral characteristics in our dataset and *complexityindex*. The coefficient on *complexityindex* indicates that a one standard deviation increase in complexity is associated with a 68 basis point increase in the foreclosure rate in a pool. The coefficient on *complexityindex* is significant at the 1% level. Because we control for the year of issuance of the deal, the relation between complexity and collateral quality that we uncover is not being driven by the fact that, over our sample period, complexity is increasing (see Figure 1) while collateral quality is decreasing. There is thus a positive association between *ex post* collateral quality and complexity. This finding is analogous to Furfine's (2014) in the CMBS market. When we use *collatlossshare* as the dependent variable (Columns 3 and 4), the coefficient on *compleixtyindex* is positive but far from statistically significant. However, the sample of loan groups for which we have the variable *collatlossshare* is smaller and so the lack of a relation may be merely a power issue.

Nevertheless, taken in isolation, a finding that lower quality collateral is associated with more complexity reveals little because investors hold the securities not the collateral. Rather, the promise of complex structuring was to create high quality securities from low quality collateral. More complexity may be necessary to provide greater protection for the senior tranches in deals with lower quality collateral. It is our finding of greater *security* default that makes the relation between higher foreclosure rates and complexity seem more suspect.

Given that the relation between complexity and security performance persists after controlling for collateral performance, a further possibility is that complexity disadvantages senior tranches regardless of the underlying collateral quality. PLMBS waterfalls typically provide mechanisms whereby payments to a subordinate class can be accelerated. Horwitz (2011) details one such example of shifting interests involving Carrington Capital Management. In essence, Carrington's actions as servicer, for example, liberally using capitalization modifications to make loans current, allowed it to release millions of dollars of excess spread to the equity tranche that it owned rather than to the deal's senior tranche. More generally, Whitworth and Walsh (2006) document a myriad of triggers in equity MBS deals and resulting "flip-flops" all of which have the potential to reduce the degree of protection afforded to senior tranches. While these junior securities almost all defaulted eventually, they received more cashflows in the early years of the deal, thereby denying senior securities protection and increasing their subsequent default likelihood.

To test this conjecture, we first construct a deal-level variable, *ResidgotCFs* that takes a value of one if a residual tranche in the deal receives any cashflows. In approximately 27% of the deals in our sample, the residuals received cashflows. As Columns 1 and 2 of Table 10 show, this variable is strongly associated with the rated tranches defaulting. Column 1 presents the marginal effects from a regression of *default* on *ResidgotCFs* and our standard control variables when we include all tranches; Column 2 presents the same specification when we include only securities rated AAA at issuance. The coefficient on *ResidgotCFs* in both samples is significant at the 1% level. The magnitude of the estimate indicate that, when the residual tranches of the deal received cashflows, a security is 3 percentage points more likely to default. In the AAA sample, a residual tranche receiving cashflow increases the risk of default by 9 percentage points (21%).

Column 3 shows further that the residuals were much more likely to get cash flows if the deal was more complex. A one standard deviation increase in complexity is associated with a 10 percentage point (35%) higher chance the residual got any cash flows. Thus, the more complex deals have a mechanism that advantages the junior claimants in a deal at the expense of the more senior tranche holders.

As noted by Gorton (2008), subprime mortgages were typically securitized by "XS/OC" structures.[9] Credit enhancement in "XS/OC" deals is dynamic and depends on the performance of the underling subprime collateral. In particular, given the availability of a large excess spread in subprime deals, over-collateralization is accumulated over time by diverting excess spread to initially pay down only senior tranches. Once an over-collateralization target is reached, the junior tranches are entitled to receive excess spread if various triggers are passed. These triggers include delinquency triggers and cumulative loss triggers. Failing a trigger prevents the paying down of the subordinate bonds, thereby averting a reduction of credit enhancement for the senior bonds. Otherwise, the credit enhancement levels of the subprime deal are allowed to decline or "step down" and the senior bonds' subordination

[9]Here OC denotes over-collateralization while XS represents excess spread. By contrast, prime mortgages were securitized by "shifting interest/senior-sub" deals also referred to as "six-pack" structures because they include three mezzanine bonds and three subordinate bonds junior to the AAA bonds in a deal.

is reduced by paying the lower tranches in *reverse* order of seniority. While beneficial to the lower tranches, our results confirm that this diversion of cash flows was costly to senior tranches as the credit enhancement they surrendered was unavailable when house prices fell dramatically post-2006.[10]

6. The Pricing of Complexity

Given that complex deals perform worse *ex post*, it is important to see how investors price complexity *ex ante* to ascertain whether they were aware that more complex securities were more likely to perform poorly. We analyze the pricing of complexity by regressing the yield spread of securities on various determinants. More specifically, let Y_i be the yield of security i at issuance in excess of one month LIBOR. Our goal is to see whether more complex securities, as measured by our complexity variables, had higher yields.

We run the following cross-sectional regression

$$Y_i = Complex'_{i,j}\gamma_1 + Controls'_{i,j}\gamma_2 + \varepsilon_i \tag{2}$$

where, as before, $Complex_{i,j}$ is a vector of complexity variables for security i in deal j and $Controls_{i,j}$, are control variables, observable at origination of security i, and j indexes either the deal or the group.

Table 11 presents the results from estimating equation (2). The coefficients are mostly statistically insignificant and the magnitudes are small. A one standard deviation in *complexityindex* is associated with a reduction in spreads of 1.5 basis points and the effect is statistically significant only at the 10% level. Overall, the results indicate that investors did not perceive more complex securities to be of lower quality *ex ante*. The same is true

[10]The recent legal dispute between Prosiris Capital and Tilden Park Capital versus AIG and BlackRock (Ng and Rexrode (2017)) underscores the complexity of PLMBS and illustrates how these deals provide a mechanism to divert cash flow from senior bonds to non-senior bonds. The parties had differing views on how a subsequent principal recovery should be allocated to bonds in several Countrywide PLMBS. Under the "pay first and write down second" interpretation favored by Prosiris and Tilden Park, a deal's over-collateralization target would be met and so allowing a majority of the recovery to "leak" to lower tranches owned by the hedge funds. By contrast, AIG and BlackRock's "write down first and pay second" interpretation would result in the over-collateralization target not being met, implying that all of the recovery would be received by the senior tranches owned by AIG and BlackRock.

if we confine our analysis to AAA securities; the results for only AAA securities are in an appendix available from the authors.

As expected, AAA investors accepted lower rates of return than AA, A, or BBB investors, and AA investors were promised lower returns than A or BBB investors. Investors perceived larger deals to be less risky as well as deals in which there was more excess spread.

We perform the same sensitivity analyses for our examination of spreads and complexity as we did for default. The results are available from the authors upon request.

7. Discussion

7.1. **Complexity in the MBS Market and Security Design.** We have shown that more complex securities perform worse and that investors did not price more complex securities in a manner consistent with their perceiving them to be riskier. Can we reconcile our results with theories of security design? We evaluate the consistency of our results with two classic theories, "tailoring theory" and "information sensitivity theory". Perhaps most importantly, neither theory can explain why securities from more complex deals perform worse.

Allen and Gale's (1988) seminal theory of complexity, which we term tailoring theory, posits that complexity arises to complete the market in the Arrow-Debreu sense. In tailoring theory, an issuer (a trust in our case) should offer many different types of securities collateralized by the same assets (a pool of mortgages in our case) that satisfy different investor appetites. In so doing, investors maximize the revenue the issuer receives from the sale of the securities because each security is held by the investor that values it most.[11]

The tailoring theory of complexity is consistent with the existence of loan groups structured specifically to satisfy the GSEs' demand. However, for the tailoring theory to explain the substantial complexity that we document, the different loan groups within deals would have to be dissimilar to one another. That is, the collateral must be customized within a deal to satisfy particular clients' requests for specific types of collateral resulting in substantively dissimilar loan groups within a deal. If the loan groups are quite similar to one another,

[11] Allen and Gale (1991) extend their completing the market argument to a market model with short sales. In general, investors cannot short MBS. Since 2006, investors can short indices of MBS via the ABX.

spanning different states of the world cannot be the main reason for the different loan groups since investors within a deal are buying assets backed by effectively the same collateral.

To test for tailoring, we compare the within deal differences in loan characteristics to the differences in loan characteristics across deals originated in the same year. In the absence of tailoring, we expect the two measures to be roughly equal. We compute the mean absolute deviation (MAD) of several loan characteristics between groups within a deal and across deals. That is, for each loan characteristic c, we compute

$$DiffIntra^c = \frac{1}{N}\sum_{k=1}^{N}\left|Char^c_{k,j} - \frac{1}{N_j}\sum_{n=1}^{N_j} Char^c_{k,j}\right|$$

and

$$DiffInter^c = \frac{1}{N}\sum_{k=1}^{N}\left|Char^c_{k,j} - \frac{1}{N_T}\sum_{l=1}^{N_T} Char^c_{l,j}\right|$$

where N is the total number of loan groups in our data, N_T is the total number of loan groups in year T, and N_j is the total number of loan groups in deal j. If the division into loan groups is because of tailoring, we expect $DiffIntra^c > DiffInter^c$.

Table 12 compares the differences between loan groups within deals and the differences between loan groups across deals. There is much more variation in loan characteristics across deals than within them. The largest amount of variation in loan group characteristics within deals is in the original principal balances. The intra-deal differences in principal balances are likely due to the influence of the GSEs and, even along this dimension, there is greater variation across deals than within deals. Thus, tailoring cannot explain a substantial portion of the complexity creating by subdividing the loan pool into separate loan groups.[12]

[12]Furthermore, the Allen and Gale theory of complexity is somewhat difficult to apply to the MBS market since, unlike a corporation, the underlying assets in a trust that issues mortgage-backed securities are inherently more divisible than a corporation. Should an MBS consist of 1000 loans or 5000 loans? Some pooling of loans can be explained by diversification benefits (DeMarzo, 2005) and the desire to overcome adverse selection created by the originator of the loans (not necessarily of the securities) having more information than investors (Riddiough (1997) and DeMarzo (2005)). Without additional theory, however, it is difficult to understand why so many securities are issued within one deal rather than issued from separate deals. It is possible that there is some high fixed cost of issuing a deal such that it is advantageous to issue very large deals with more securities and loan groups rather than put the different loan groups into separate deals. Certainly, it seems likely that there are costs to establishing a trust (e.g., legal fees) that are not present with subdividing loans within a deal. However, it is unclear what puts an upper bound on the number of loans within a pool if the fixed costs are very high.

Another strand of the literature, pioneered by Gorton and Pennacchi (1990) and Boot and Thakor (1993), posits that the multiple securities we observe can be explained by the need for some securities to be informationally insensitive or at least less informationally sensitive. Consistent with the theory of information sensitivity, MBS deals include both informationally sensitive securities (i.e., securities with ratings below AAA) and less informationally less sensitive securities (i.e., securities with AAA ratings). Unfortunately, the information sensitivity model does not provide a prediction as to how many different securities an asset should collateralize, only that there should be differences in the information sensitivity of the securities that are issued. What is difficult to understand is why it is necessary to have so many different informationally sensitive and informationally insensitive securities within the same deal.

In summary, several facts we uncover about complexity are difficult to reconcile with traditional theories of security design including those that allow explicitly for informational asymmetry between the issuer of a security and investors. Our results suggest that issuers use complexity to strategically increase search costs for prospective buyers. The most closely related work is in industrial organization models wherein firms can obfuscate prices to retain clients (see Ellison and Ellison (2009), Carlin (2009), and Ellison and Wolitzky (2012)).

While we do not have direct evidence regarding the underwriters' intent, a useful direction for future research may be to explore whether complexity is a complement or a substitute for the types of misreporting found by Ben-David (2011), Jiang, Nelson, and Vyltacil (2014), Piskorski, Seru, and Witkin (2015), and Griffin and Maturana (2016).

7.2. **Who Issues Complex Securities?** Table 13 shows the five most complex issuers in each year from 2003 through 2006. While our findings regarding security performance are not driven solely by heterogeneity across issuers in the degree of complexity (see Column 6 of Table 8), there is substantial persistence in complexity across issuers. For example, Countrywide is one of the two most complex lead managers in all four years. Similarly, Lehman Brothers is one of the three most complex lead managers in every year.

One may also wonder whether the negative relation between complexity and security performance is driven only by a few issuers varying the level of complexity in their deals or whether it is common to many lead managers. To explore this question, we estimate a specification of equation (1) in which we allow the relation between complexity and security performance to vary across lead managers. To do so, we confine our sample to securities issued in 2003-2006 by the top 10 lead managers by dollar volume. We then include *complexityindex* separately for each lead manager by including it as an interaction with the lead manager fixed effect. Column 2 presents our benchmark probit for default when we include *complexityindex* separately for each issuer for all securities in our sample; Column 3 contains the same specification but including issuer fixed effects in levels. In both specifications, the coefficients on *complexityindex* are positive for all issuers although only statistically significant for seven of them. In columns 5 and 6, we present the results for only securities rated AAA at issuance. In the AAA sample, the coefficients are positive for eight of the ten lead managers and statistically significant for four of them. It thus seems that the negative relation between complexity and security performance is broad-based rather than only driven by a small subset of issuers.

8. Conclusion

We propose measures of complexity for structured finance securities. We apply our measures to the nonprime MBS market and document an increase in complexity in the 2000s. We then show that an increase in complexity is robustly associated with a higher likelihood of default and lower realized rates of return. The increase in the risk of default associated with complexity is greatest for securities designed to be informationally insensitive. Lower *ex post* quality collateral is associated with greater complexity but securities from more complex deals default more even after controlling for the realized collateral quality. *Ex ante* pricing indicates that investors did not think more complex securities would default more although several aspects of MBS risk beyond credit ratings were priced.

Going forward, our results suggest that, by reducing search costs, standardizing the market for certain types of securities could benefit investors although a full welfare analysis is beyond the scope of this paper. While most of the theoretical literature focuses on sellers increasing the costs for buyers to discover the price of the security, our findings highlight that an alternative way to affect the quality-adjusted price is to make it harder for prospective buyers to learn the quality of the product. Finally, our work shows the need for models of security design that incorporate the ability of issuers to affect investors' search costs.

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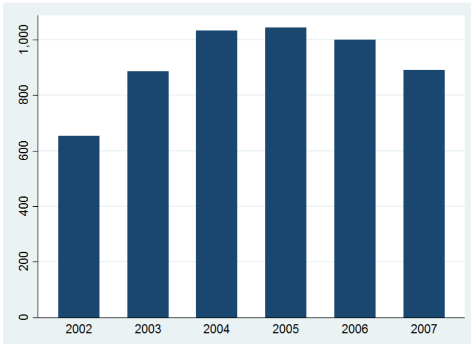
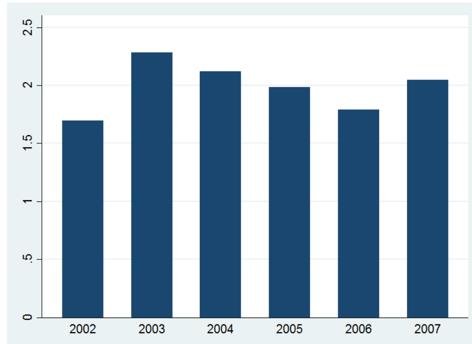
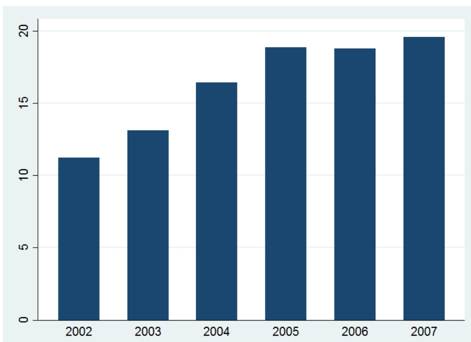
Figure 1. Means of Deal Size and Complexity Variables by Year, 2002-2007



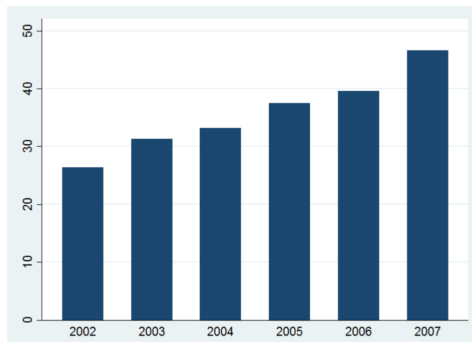
(a) Deal Size ($M)



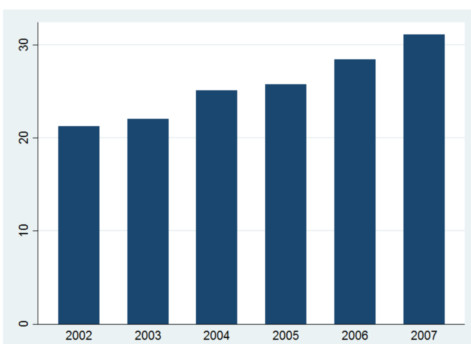
(b) No. of Loan Groups



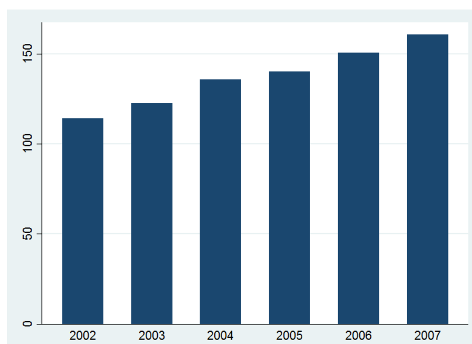
(c) No. of Securities



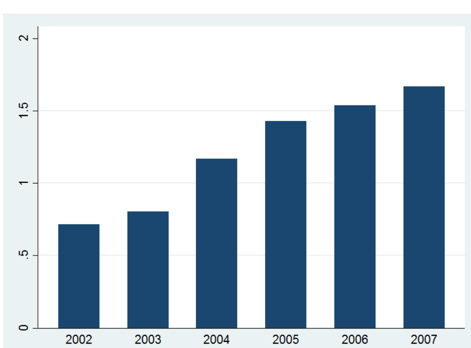
(d) No. of Pages Describing Collateral



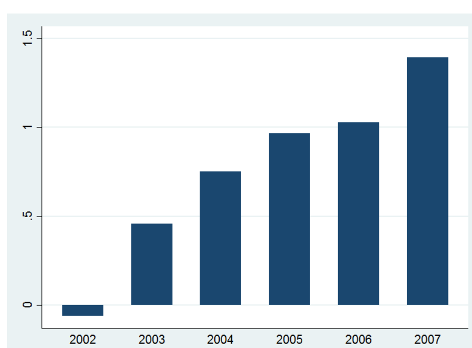
(e) No. of Pages Describing Waterfall



(f) No. of Terms in Glossary



(g) File Size of Prosup (MB)



(h) Complexity Index

Table 1. Summary Statistics on Complexity Variables (by Deal)

Panel A: Individual Complexity Variables:					
Variable	Obs	Mean	Std. Dev.	Min	Max
nloangroups	1,299	2.0	0.9	1	11
ntranches	1,299	17.8	5.2	2	68
pagesmpool	1,293	37.9	17.5	4	148
pageswaterfall	1,294	26.8	9.1	1	62
nglossaryterms	1,289	143.6	72.2	27	431
filesizemb	1,299	1.4	1.5	0.1	34.2
complexityindex	1,282	0.9	1.0	-1.1	10.2
Panel B: Complexity Index by Year:					
Year	Mean	Std. Dev.	p25	p50	p75
2002	-0.06	0.56	-0.34	-0.08	0.37
2003	0.46	0.86	-0.03	0.37	0.82
2004	0.75	0.85	0.22	0.68	1.11
2005	0.97	0.91	0.37	0.93	1.29
2006	1.03	0.88	0.41	0.95	1.46
2007	1.39	1.11	0.74	1.26	1.76
All Years	0.93	0.96	0.30	0.86	1.38

Notes: 1) These variables vary at the deal level such that the unit of observation in the table is a deal. 2) The variable definitions are as follows: *nloangroups* is the number of loan groups in the deal; *ntranches* is the number of securities in the deal; *pagesmpool* is the number of pages in the prospectus supplement describing the collateral; *pageswaterfall* is the number of pages in the prospectus supplement describing the allocation of payments from the collateral to the securities; *nglossaryterms* is the number of individual terms in the glossary; *filesizemb* is the size of the propsectus supplement in megabytes; *complexityindex* is the normalized first principal component of *nloangroups*, *ntranches*, *pagesmpool*, *pageswaterfall*, *nglossaryterms*, and *filesizemb*; 3) The sample is all USD-denominated private-label ABS deals backed by US collateral issued 2002-2007 for which detailed information is available via Bloomberg.

TABLE 2. Correlations Between Complexity Variables

	dealsize	*nloangroups*	*ntranches*	*pagesmpool*	*pageswaterfall*	*nglossaryterms*	*filesizemb*
dealsize	100%						
nloangroups	31%	100%					
ntranches	34%	51%	100%				
pagesmpool	28%	41%	27%	100%			
pageswaterfall	18%	27%	39%	20%	100%		
nglossaryterms	17%	26%	29%	15%	11%	100%	
filesizemb	4%	2%	10%	14%	1%	3%	100%

Notes: 1) Complexity variables measured are measured at the deal-level such that we use one observation per deal to compute correlations shown. *nloangroups* is the number of loan groups in the deal, *ntranches* is the number of securities in the deal, *pagesmpool* is the number of pages in the prospectus supplement describing the collateral,*pageswaterfall* is the number of pages in the prospectus supplement describing the allocation of payments from collateral to the securities, *nglossaryterms* is the number of terms in the glossary of the prospectus supplement, and *filesizemb* is the size of the prospectus file in megabytes.

TABLE 3. Summary Statistics on Security Performance

Variable	Obs	Mean	p10	p25	p50	p75	p90
default	15,922	0.74					
AAA_default	5,651	0.42					
AA_default	3,717	0.84					
A_default	3,326	0.97					
BBB_default	3,228	0.97					
IRR	12,490	-13.7	-76.2	-5.3	1.9	3.3	4.5
AAA_IRR	5,444	1.5	-0.1	1.4	2.2	3.5	4.3
AA_IRR	2,859	-21.1	-83.5	-57.3	1.9	2.5	3.3
A_IRR	2,158	-26.9	-86.7	-67.2	1.5	3.8	4.8
BBB_IRR	2,029	-29.8	-87.0	-70.7	-5.8	4.2	5.9

Notes: 1) *default* takes a value of one if the security has defaulted by summer 2013. 2) IRRs are winsorized at the 1% level and not computed for interest-only or principal-only securities. 3) *AAA_default* is *default* computed over the set of securities that are rated AAA; *AAA_IRR* is computed similarly as are the variables with prefixes of other rating categories. 4) The unit of observation in the table is a security.

Table 4. Complexity and Security Default

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	*default*	*default*	*default*	*default*	*default*	*default*	*default*	*default*
nloangroups	0.027***						0.019***	
	(0.0055)						(0.0064)	
ntranches		0.0026***					0.00045	
		(0.00097)					(0.0011)	
pagesmpool			0.00073***				0.00039*	
			(0.00020)				(0.00022)	
pageswaterfall				0.00100***			0.00044	
				(0.00038)			(0.00041)	
nglossaryterms					0.00030***		0.00026***	
					(0.000054)		(0.000053)	
filesizemb						0.0082**	0.0067***	
						(0.0034)	(0.0026)	
complexityindex								0.035***
								(0.0052)
dealsize	0.000021***	0.000025***	0.000029***	0.000031***	0.000030***	0.000030***	0.000021***	0.000019***
	(6.1e-06)	(6.8e-06)	(6.1e-06)	(6.1e-06)	(5.8e-06)	(6.1e-06)	(6.2e-06)	(6.1e-06)
crosscollat	-0.020***	-0.014**	-0.014**	-0.0097	-0.021***	-0.010	-0.031***	-0.026***
	(0.0071)	(0.0070)	(0.0069)	(0.0068)	(0.0070)	(0.0069)	(0.0072)	(0.0070)
excessspread	-0.00071	0.0028	0.0048*	0.0037	0.0036	0.0061**	-0.0038	-0.0044
	(0.0032)	(0.0031)	(0.0027)	(0.0029)	(0.0027)	(0.0027)	(0.0032)	(0.0032)
leadtot	1.0e-07	1.0e-07	8.8e-08	2.2e-07	-3.3e-07	1.6e-07	-2.5e-07	-3.3e-08
	(2.0e-07)	(2.0e-07)	(2.1e-07)	(2.1e-07)	(2.2e-07)	(2.0e-07)	(2.2e-07)	(2.0e-07)
subordination	-0.0066***	-0.0070***	-0.0067***	-0.0069***	-0.0066***	-0.0068***	-0.0064***	-0.0066***
	(0.00079)	(0.00082)	(0.00078)	(0.00081)	(0.00080)	(0.00082)	(0.00077)	(0.00076)
spread	0.00027***	0.00028***	0.00031***	0.00031***	0.00025**	0.00027***	0.00028***	0.00030***
	(0.00011)	(0.00011)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)
disagreetranche	0.052***	0.051***	0.052***	0.052***	0.054***	0.050***	0.054***	0.053***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Observations	14,556	14,556	14,480	14,480	14,446	14,556	14,357	14,357
Std. Err. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating at Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top 5 State Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.52	0.52	0.52	0.52	0.52	0.52	0.53	0.53

Notes: 1) Entries shown are marginal effects from probit estimation of default on variables shown. 2) See appendix for variable definitions. 3) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 4) The unit of observation is a security. 5) Standard errors are clustered by deal.

Table 5. Complexity and Realized Returns on Securities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*
nloangroups	-1.00*						0.85	
	(0.55)						(0.71)	
ntranches		-0.28**					-0.28**	
		(0.11)					(0.14)	
pagesmpool			-0.054**				-0.064**	
			(0.025)				(0.028)	
pageswaterfall				-0.10**			-0.065	
				(0.051)			(0.054)	
nglossaryterms					-0.021***		-0.020***	
					(0.0059)		(0.0060)	
filesizemb						-0.098	-0.020	
						(0.28)	(0.24)	
complexityindex								-2.30***
								(0.58)
dealsize	-0.0016***	-0.0014**	-0.0016***	-0.0016***	-0.0018***	-0.0020***	-0.00094	-0.00091
	(0.00058)	(0.00060)	(0.00061)	(0.00062)	(0.00058)	(0.00057)	(0.00065)	(0.00063)
crosscollat	0.37	0.49	0.16	-0.14	0.78	-0.026	1.07	0.95
	(0.82)	(0.83)	(0.79)	(0.77)	(0.78)	(0.77)	(0.86)	(0.83)
excessspread	0.26	0.41	0.037	0.18	0.19	-0.0082	0.54	0.69*
	(0.33)	(0.33)	(0.30)	(0.32)	(0.31)	(0.29)	(0.36)	(0.36)
leadtot	0.000034	0.000034	0.000034	0.000022	0.000064**	0.000033	0.000059**	0.000040
	(0.000028)	(0.000028)	(0.000028)	(0.000028)	(0.000029)	(0.000028)	(0.000030)	(0.000029)
subordination	0.72***	0.74***	0.73***	0.74***	0.71***	0.74***	0.72***	0.71***
	(0.15)	(0.15)	(0.15)	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)
spread	0.071***	0.071***	0.071***	0.070***	0.069***	0.071***	0.069***	0.069***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
disagreetranche	-4.93***	-4.81***	-4.75***	-4.85***	-5.20***	-4.86***	-4.94***	-4.95***
	(1.30)	(1.30)	(1.30)	(1.30)	(1.30)	(1.30)	(1.30)	(1.30)
Constant	-26.7***	-26.2***	-25.7***	-25.1***	-25.1***	-26.4***	-23.1***	-31.1***
	(3.37)	(3.39)	(3.41)	(3.41)	(3.41)	(3.39)	(3.46)	(3.59)
Observations	11,379	11,379	11,303	11,310	11,342	11,379	11,260	11,260
Std. Err. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating at Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.42	0.42	0.42	0.42	0.42	0.42	0.43	0.43

Notes: 1) Entries shown are coefficients from OLS regrssion of Internal Rates of Return IRRs on variables shown. 2) See appendix for variable definitions. 3) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 4) The unit of observation is a security. 5) Standard errors are clustered by deal. 6) Dependent variable is winsorized at the 1% level.

Table 6. Complexity and Security Default after Controlling for Collateral Performance

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*default*	*default*	*default*	*default*	*default*	*default*
complexityindex	0.036***	0.033***	0.031***	0.028***	0.026***	0.019***
	(0.0053)	(0.0052)	(0.0052)	(0.0066)	(0.0065)	(0.0066)
foreclosurerate		0.0026***			0.0033***	
		(0.00071)			(0.00076)	
collatlossshare			0.74***			0.72***
			(0.075)			(0.10)
dealsize	0.019***	0.019***	0.018***	0.0088	0.0096	0.0096
	(0.0062)	(0.0061)	(0.0058)	(0.0084)	(0.0082)	(0.0099)
crosscollat	-0.025***	-0.027***	-0.034***	-0.017*	-0.019**	-0.0077
	(0.0070)	(0.0071)	(0.0081)	(0.0089)	(0.0089)	(0.014)
excessspread	-0.46	-0.56*	-0.93***	-0.016	-0.096	-0.81**
	(0.33)	(0.33)	(0.33)	(0.40)	(0.40)	(0.40)
leadtot	-0.0046	0.0036	0.011	-0.027	-0.016	-0.0096
	(0.020)	(0.020)	(0.022)	(0.025)	(0.025)	(0.028)
AAA Rated	-0.26***	-0.26***	-0.27***	-0.17***	-0.16***	-0.17***
	(0.023)	(0.023)	(0.027)	(0.038)	(0.037)	(0.035)
AA Rated	-0.091***	-0.089***	-0.11***	-0.044	-0.042	-0.074***
	(0.019)	(0.019)	(0.021)	(0.030)	(0.030)	(0.027)
A Rated	0.041**	0.041***	0.022	0.084***	0.086***	0.053**
	(0.016)	(0.016)	(0.017)	(0.026)	(0.026)	(0.025)
subordination	-0.67***	-0.69***	-0.54***	-0.73***	-0.73***	-0.39***
	(0.077)	(0.079)	(0.088)	(0.10)	(0.11)	(0.086)
spread	0.028***	0.028***	0.012	0.051***	0.051***	0.019
	(0.010)	(0.0099)	(0.010)	(0.018)	(0.018)	(0.014)
disagreetranche	0.053***	0.053***	0.055***	0.052***	0.053***	0.053***
	(0.010)	(0.010)	(0.010)	(0.014)	(0.014)	(0.013)
Observations	14,152	14,152	9,463	7,581	7,581	4,291
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes
Top 5 State Shares	Yes	Yes	Yes	Yes	Yes	Yes
Detailed Collat. Controls	No	No	No	Yes	Yes	Yes
Std. Errors Clustered by Deal	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.52	0.53	0.52	0.49	0.50	0.43

Notes: 1) Entries shown are marginal effects from probit estimation of default on variables shown. 2) See the appendix for variable definitions. 3) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 4) Detailed Collat. Controls are *ltv*, *fico*, *lownodocshare*, *balunder300kshare*, *bal300600kshare*, and *wam*. 5) The unit of observation is a security.

Table 7. Complexity and Security Default: AAA Securities Only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	*default*	*default*	*default*	*default*	*default*	*default*	*default*	*default*
nloangroups	0.066***						0.047***	
	(0.013)						(0.015)	
ntranches		0.0040*					-0.0014	
		(0.0022)					(0.0024)	
pagesmpool			0.0020***				0.0011***	
			(0.00040)				(0.00040)	
pageswaterfall				0.0020**			0.0010	
				(0.00089)			(0.00089)	
nglossaryterms					0.00066***		0.00054***	
					(0.00012)		(0.00012)	
filesizemb						0.015**	0.012***	
						(0.0066)	(0.0044)	
complexityindex								0.077***
								(0.012)
dealsize	0.041***	0.057***	0.055***	0.062***	0.061***	0.063***	0.041***	0.036**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
crosscollat	-0.052***	-0.033**	-0.041***	-0.025*	-0.046***	-0.029**	-0.069***	-0.061***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)
excessspread	0.44	1.70**	2.06***	1.79***	1.66***	2.28***	0.14	-0.25
	(0.67)	(0.67)	(0.56)	(0.58)	(0.54)	(0.56)	(0.68)	(0.67)
leadtot	0.055	0.051	0.053	0.082*	-0.050	0.065	-0.018	0.024
	(0.040)	(0.041)	(0.042)	(0.044)	(0.043)	(0.041)	(0.043)	(0.040)
subordination	-1.05***	-1.16***	-1.10***	-1.14***	-1.08***	-1.13***	-0.99***	-1.07***
	(0.18)	(0.18)	(0.18)	(0.19)	(0.19)	(0.19)	(0.18)	(0.18)
spread	0.70***	0.71***	0.73***	0.71***	0.70***	0.71***	0.69***	0.69***
	(0.12)	(0.11)	(0.12)	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)
disagreetranche	0.031	0.024	0.019	0.022	0.040	0.025	0.037	0.024
	(0.045)	(0.045)	(0.046)	(0.045)	(0.045)	(0.045)	(0.044)	(0.045)
Observations	4,944	4,944	4,911	4,911	4,908	4,944	4,870	4,870
Std. Errors Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top 5 State Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.40	0.39	0.39	0.39	0.40	0.39	0.41	0.40

Notes: 1) Entries shown are marginal effects from probit estimation of default on variables shown. 2) See the appendix for variable definitions. 3) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 4) The unit of observation is a security. 5) Standard errors are clustered by deal.

Table 8. Complexity and Security Default: Sensitivity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	*default*	*default*	*default*	*default*	*default*	*default*	*default*	*default*
complexityindex	0.035***	0.077***	0.0099**	0.029***	0.031***	0.029***	0.028***	0.026***
	(0.0052)	(0.012)	(0.0050)	(0.0067)	(0.0051)	(0.0057)	(0.0047)	(0.0065)
AAA Rated	-0.26***			-0.16***	-0.26***	-0.28***	-0.24***	-0.29***
	(0.023)			(0.037)	(0.023)	(0.023)	(0.028)	(0.023)
AA Rated	-0.087***		-0.099***	-0.042	-0.087***	-0.10***	-0.076***	0.010
	(0.019)		(0.013)	(0.030)	(0.019)	(0.020)	(0.023)	(0.016)
A Rated	0.042***		-0.0026	0.084***	0.040***	0.033**	0.059***	0.082***
	(0.016)		(0.010)	(0.026)	(0.015)	(0.016)	(0.019)	(0.0097)
Constant								0.57***
								(0.044)
Observations	14,357	4,870	9,487	7,619	13,705	12,928	13,370	14,357
Std. Errors Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Benchmark Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Qtr of Issue FEs	No	No	No	No	No	No	Yes	No
Top 5 State Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Includes Conforming Pools	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Detailed Collat. Controls	No	No	No	Yes	No	No	No	No
AAA Only	No	Yes	No	No	No	No	No	No
Lead Manager FEs	No	No	No	No	No	Yes	No	No
Pseudo R^2	0.53	0.40	0.37	0.49	0.52	0.53	0.55	
R^2								0.46

Notes: 1) Entries shown in Columns 1-7 are marginal effects from probit estimation of default on variables shown. 2) Entries shown in Column 8 are coefficients from OLS estimation of default on the variables shown. 3) See the appendix for variable definitions. 3) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 4) Collateral Characteristics are *ltv*, *fico*, *lownodocshare*, *balunder300kshare*, *bal300600kshare*, and *wam*. 5) In the specification in Column 5, we exclude securities collateralized primarily by loan groups indicated as conforming in the loan group description from Bloomberg. 6) In the specification in Column 6, we include only deals from the top 15 issuers by volume and include fixed effects for each of these issuers. 7) In the specification in Column 7, we include only deals issued 2004-2007 as there are too few observations in some quarters in the earlier year to include year fixed effects. 8) The unit of observation is a security. 9) Standard errors are clustered by deal. 10) Benchmark controls are *dealsize*, *crosscollat*, *excessspread*, *leadtot*, *subordination*, *spread*, and *disagreetranche*.

Table 9. Complexity and Collateral Default

	(1)	(2)	(3)	(4)
Dep. Var.	*foreclosurerate*	*foreclosurerate*	*collatlossshare*	*collatlossshare*
complexityindex	0.68***	0.69***	0.0022	0.0015
	(0.22)	(0.22)	(0.0026)	(0.0040)
dealsize	0.000015	-6.0e-06	7.3e-07	9.5e-06
	(0.00024)	(0.00037)	(3.3e-06)	(7.3e-06)
crosscollat	0.90***	0.23	0.00068	-0.021
	(0.32)	(0.43)	(0.0052)	(0.016)
excessspread	0.37***	0.16	0.0012	0.0024
	(0.12)	(0.12)	(0.0019)	(0.0026)
leadtot	-0.000045***	-0.000038***	-3.1e-07**	-9.4e-08
	(9.8e-06)	(0.000012)	(1.5e-07)	(3.0e-07)
Constant	4.53***	36.1***	-0.015	-0.039
	(1.17)	(8.97)	(0.017)	(0.17)
Observations	2,180	1,139	1,027	338
R-squared	0.36	0.44	0.78	0.72
Year of Issue FEs	Yes	Yes	Yes	Yes
Detailed Collat. Controls	No	Yes	No	Yes
Std. Errors Clustered by Deal	Yes	Yes	Yes	Yes

Notes: 1) Entries shown in columns 1 and 2 are coefficients from a regression of the foreclosure rate on the loan group, in percent, on the variables shown. 2) Entries shown in columns 3 and 4 are coefficient from a regression of the overall loss rate (a combination of the foreclosure rate and the loss given foreclosure) on the collateral on the variables shown. 3) See the appendix for variable definitions. 4) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 5) Detailed Collat. Controls are *ltv*, *fico*, *lownodocshare*, *balunder300kshare*, *bal300600kshare*, and *wam*. 6) The unit of observation is a loan group.

Table 10. Residual Cashflows and Deal Complexity

	(1)	(2)	(3)
Dep. Var.	*default*	*default*	*ResidgotCFs*
ResidgotCFs	0.032***	0.089***	
	(0.0078)	(0.018)	
complexityindex			0.096***
			(0.017)
dealsize	0.000025***	0.000053***	0.000076***
	(6.0e-06)	(0.000013)	(0.000023)
crosscollat	0.0046	0.0053	-0.32***
	(0.0070)	(0.015)	(0.028)
excessspread	0.0034	0.019***	-0.031***
	(0.0027)	(0.0055)	(0.011)
leadtot	2.0e-07	9.4e-07**	-4.2e-06***
	(2.0e-07)	(4.3e-07)	(8.5e-07)
AAA Rated	-0.28***		
	(0.023)		
AA Rated	-0.11***		
	(0.019)		
A Rated	0.032*		
	(0.017)		
subordination	-0.0060***	-0.0100***	
	(0.00077)	(0.0020)	
spread	0.00014	0.0069***	
	(0.000093)	(0.0012)	
disagreetranche	0.051***	0.033	
	(0.0098)	(0.047)	
Observations	14,478	4,702	1,149
Std. Errors Clustered by Deal	Yes	Yes	NA
Year of Issue FEs	Yes	Yes	Yes
Top 5 State Shares	Yes	Yes	NA
AAA only	No	Yes	NA
Pseudo R^2	0.53	0.40	0.12

1) Entries shown are marginal effects from probit estimation of the dependent variable indicated on variables shown. 2) See appendix for variable definitions. 3) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 4) The unit of observation in Columns 1 and 2 is a security. 5) Standard errors in Columns 1 and 2 are clustered by deal. 6) The unit of observation in Column 3 is a deal.

Table 11. Security Spreads and Security Complexity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	*spread (bp)*	*spread (bp)*	*spread (bp)*	*spread (bp)*	*spread (bp)*	*spread (bp)*	*spread (bp)*
nloangroups	-1.18						
	(0.85)						
ntranches		-0.14					
		(0.15)					
pagesmpool			-0.053				
			(0.038)				
pageswaterfall				0.027			
				(0.084)			
nglossaryterms					-0.026**		
					(0.011)		
filesizemb						0.045	
						(0.16)	
complexityindex							-1.46*
							(0.87)
dealsize	-0.0022**	-0.0024**	-0.0022**	-0.0026**	-0.0025**	-0.0027***	-0.0018*
	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.00098)	(0.00098)	(0.0011)
crosscollat	-0.058	-0.30	-0.14	-0.46	0.57	-0.58	0.40
	(1.44)	(1.41)	(1.43)	(1.39)	(1.49)	(1.38)	(1.51)
excessspread	-1.27**	-1.39***	-1.60***	-1.73***	-1.36***	-1.62***	-1.15**
	(0.54)	(0.53)	(0.44)	(0.48)	(0.46)	(0.44)	(0.57)
leadtot	-0.000015	-0.000015	-0.000012	-0.000012	0.000026	-0.000016	-4.4e-06
	(0.000035)	(0.000035)	(0.000035)	(0.000037)	(0.000035)	(0.000035)	(0.000034)
AAA Rated	-178***	-179***	-179***	-179***	-178***	-179***	-178***
	(5.03)	(4.96)	(4.97)	(4.91)	(5.11)	(4.92)	(5.13)
AA Rated	-154***	-154***	-154***	-154***	-153***	-154***	-154***
	(2.75)	(2.72)	(2.73)	(2.69)	(2.81)	(2.70)	(2.81)
A Rated	-108***	-108***	-109***	-109***	-108***	-109***	-109***
	(1.43)	(1.42)	(1.42)	(1.41)	(1.45)	(1.42)	(1.45)
subordination	-0.18	-0.17	-0.16	-0.15	-0.18	-0.16	-0.16
	(0.30)	(0.29)	(0.29)	(0.29)	(0.30)	(0.29)	(0.30)
disagreetranche	14.3***	14.3***	14.2***	14.1***	14.1***	14.3***	14.2***
	(1.51)	(1.50)	(1.50)	(1.50)	(1.51)	(1.50)	(1.51)
Constant	246***	246***	246***	246***	247***	246***	242***
	(5.38)	(5.34)	(5.35)	(5.40)	(5.37)	(5.34)	(5.89)
Observations	14,556	14,556	14,480	14,480	14,446	14,556	14,357
R-squared	0.76	0.76	0.76	0.76	0.76	0.76	0.76
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top 5 State Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Entries shown are coefficients from a regression of the spread of the security, in basis points, relative to one month LIBOR on the variables shown. 2) See the appendix for variable definitions. 3) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 4) The unit of observation is a security. 5) Standard errors are clustered by deal.

TABLE 12. Are Loan Groups Tailored?

Loan Group Characteristic	Inter-Deal MAD	Intra-Deal MAD	T-Stat for Difference
Cashare	12.2	7.4	20.6
Flshare	2.9	1.3	23.4
Nyshare	3.7	1.3	36.4
Ilshare	3.1	1.3	38.0
Txshare	2.6	0.9	38.8
fico	20.1	7.3	22.3
ltv	3.5	0.9	22.4
lownodocshare	17.8	3.3	33.2
balunder300kshare	18.5	17.2	3.3
bal300600kshare	14.4	13.4	3.1
balover600kshare	4.8	3.9	6.5
wam	7.8	1.9	19.2

Notes: 1) MAD is mean absolute deviation of loan characteristic across loan groups. 2) For each loan characteristic c, we compute the Intra-Deal MAD as

$$DiffIntra^c = \frac{1}{N}\sum_{k=1}^{N}\left|Char^c_{k,j} - \frac{1}{N_j}\sum_{n=1}^{N_j} Char^c_{k,j}\right|$$

and the Inter-Deal MAD as

$$DiffInter^c = \frac{1}{N}\sum_{k=1}^{N}\left|Char^c_{k,j} - \frac{1}{N_T}\sum_{l=1}^{N_T} Char^c_{l,j}\right|$$

where N is the total number of loan groups in our data, N_T is the total number of loan groups in year T, and N_j is the total number of loan groups in deal j. 3) If the division into loan groups is because of tailoring, we expect $DiffIntra^c > DiffInter^c$. 4) See the appendix for variable definitions.

TABLE 13. Most Complex Lead Managers: Complexity Index by Lead Manager by Year

2003	LB	CWSC	JPM	BS	CITG	Big Lead Avg.
	1.37	1.28	0.73	0.54	0.52	0.45
2004	CWSC	LB	RGW	BCG	BS	Big Lead Avg.
	1.68	1.34	0.97	0.77	0.74	0.75
2005	CWSC	LB	DBS	JPM	BCG	Big Lead Avg.
	2.01	1.39	1.21	1.09	0.93	1.00
2006	CWSC	BS	LB	JPM	DBS	Big Lead Avg.
	1.92	1.37	1.31	1.12	1.05	1.02

Notes: 1) LB is Lehmann Brothers, CWSC is Countrywide Securities, JPM is JP Morgan, BS is Bear Stearns, CITG is Citigroup, RGW is Greenwich Capital Financial, BCG is Barclays Capital, and DBS is Deutschebank Securities. 2) A lead manager is a big lead if it ranks in the top 15 issuers by dollar volume of deals.

Table 14. Security Default and Complexity Interacted with Issuer Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*default*	*default*	*default*	*default*	*default*	*default*
complexityindex	0.042***			0.092***		
	(0.0071)			(0.015)		
complexlead1		0.022*	0.025		0.015	-0.00051
		(0.013)	(0.017)		(0.023)	(0.026)
complexlead2		0.028**	0.041*		-0.00013	0.083*
		(0.014)	(0.021)		(0.028)	(0.043)
complexlead3		0.046***	0.034**		0.071***	0.064**
		(0.012)	(0.014)		(0.022)	(0.026)
complexlead4		0.055***	0.023*		0.14***	0.027
		(0.0089)	(0.013)		(0.016)	(0.022)
complexlead5		0.052***	0.056***		0.094***	0.078**
		(0.015)	(0.015)		(0.030)	(0.038)
complexlead6		0.034**	0.046**		0.040	0.075**
		(0.013)	(0.020)		(0.026)	(0.034)
complexlead7		0.014	0.053**		0.031	0.091
		(0.017)	(0.026)		(0.034)	(0.068)
complexlead8		0.018	0.00049		-0.041	-0.088
		(0.014)	(0.028)		(0.053)	(0.075)
complexlead9		0.048***	0.030		0.087***	0.060
		(0.012)	(0.018)		(0.025)	(0.040)
complexlead10		0.0079	0.029		-0.00090	0.024
		(0.020)	(0.024)		(0.045)	(0.067)
Observations	8,472	8,472	8,472	2,918	2,918	2,918
Std. Errors Clustered	Yes	Yes	Yes	Yes	Yes	Yes
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lead Manager FEs	No	No	Yes	No	No	Yes
AAAs only	No	No	No	Yes	Yes	Yes
Pseudo R^2	0.52	0.52	0.52	0.52	0.52	0.52

Notes: 1) *complexleadi* is a dummy variable that takes a value of 1 if the lead manager is lead manager i interacted with *complexityindex*. 2) Only securities issued 2003-2006 by the top 10 lead managers by dollar volume of deals are included. 3) Other controls are those shown in Table 4. 4) The unit of observation is a security. 5) Standard errors are clustered by deal.

Appendix A. Not-for-Publication

A.1. **Data Construction Details and Summary Statistics.** Table A.1 summarizes the variables we use in our dataset and the definitions

A.1.1. *Other Deal-Level Variables.* Aside from our deal-level complexity variables, we include an indicator for whether the deal provides for cross-collateralization across loan groups, the size of the deal (in millions of USD) (*dealsize*), the excess spread in the deal in percent (*excessspread*), and the volume of ABS issuance by the lead manager of the deal in the year the deal was issued (*leadtot*). We drop a small number of deals that have negative excess spread. The lead manager is usually also the sponsor. Over most of our sample period, sponsors of the deal were not disclosed in the prospectus supplement. In 2006 deals, all PLMBS deals disclosed the sponsor, the lead manager is the sponsor about 80% of the time in the 2006 deals.

Only 34% of the deals provide for any cross-collateralization. Since more than twice that number of deals have multiple loan groups, a slight majority of deals with multiple loan groups do not provide for cross-collateralization. The average deal is for \$980 million; the smallest deal is for \$90 million and the largest deal is almost \$5 billion. The average excess spread across all securities in a deal is 3.8 percentage points. The average amount of total ABS underwriting by the lead manager of the deal in the year the deal is issued is \$30 billion, with one underwriter issuing \$75 billion of ABS in a year.[13]

We define a tranche as a residual tranche if

(1) is tranche R, CE, RX, or XR
(2) the long name of the tranche type includes the word "residual"
(3) the long name of the tranche type includes the terms "gets excess proceeds of deal"

[13]We do not include deal-level overcollateralization as a control variable because home equity ABS typically do not have any initial overcollateralization. Rather, they rely on excess spread to paydown bonds faster than simply through the return of principal, thereby creating overcollateralization. This turboing in essence converts interest into principal for the benefit of senior bonds. If a target overcollateralization amount is achieved by the deal's stepdown date, principal and interest are diverted to the residual class, provided various triggers are passed. Triggers are tests embedded in a structure to protect senior security holders if the collateral exhibits abnormally high delinquency or losses.

We then define the deal-level variable *ResidgotCFs* as equal to one if any residual in the deal received cashflows at a point subsequent to issuance and 0 otherwise.

A.1.2. *Security-Level Variables.* We control for the initial rating of the security. We include securities rated BBB through AAA and control for ratings using the ratings categories AAA, AA, A, and BBB. If there is a disagreement in the rating, we take the highest rating. For example, AAA takes a value of 1 if any of the three major CRAs rate the security AAA. Since there may be disagreement among the CRAs, we also include a dummy variable (*disagreetranche*) that takes a value of 1 if there is any disagreement among the CRAs on the rating of that tranche. The results are quite similiar when controlling for subnotches. Furthermore, there appeared to be no more information in the subnotches than in the broader ratings categories we use.

Default takes a value of 1 if the security defaults by August 2013 and 0 otherwise. We define default to be an event in which the security has suffered a principal loss or in which one of the ratings agencies indicates the security is in default. For Moody's, this is a rating of Caa1 or lower. For S&P, this is a rating of CCC+ or lower while for Fitch this is a rating of CCC or lower. Default on a security is any loss such that defaults occur for most securities in our sample despite a loan group-level foreclosure rate of 16%. The average loss on collateral, *collatlossshare* is 18% and ranges from 1% to 63%.

Panel B of Table A.1 describes our security-level variables. We include the subordination level of each security. Subordination is a measure of credit enhancement that measures the percentage of the value of all the securities in the deal that are below it in the priority of payments. Thus, AAA securities have the most subordination and BBB tranches have the least subordination. The mean level of subordination of a security in a deal is 12 percentage points.

The main pricing variable in our dataset is the fixed spread the security pays above one month LIBOR. This spread is fixed for the life of the security. Actual transaction prices are extremely difficult to observe in the ABS market since, prior to May 2011, there was no requirement that transactions be reported to any centralized body.[14] Bloomberg has transactions prices for some of our tranches on some dates, primarily the senior tranches. For dates near security issuance, the security prices are extremely close to par so that the spread is a good measure of the return investors expected to earn from investing in ABS. The mean spread on a security is 86 basis points. AAA investors were promised a mere 25 basis points while BBB investors were promised 211 basis points on average.

A.1.3. *Loan Group-Level Variables.* Our data contains the shares of each state in the top 5 most common property states for that pool. For example, if 25% of the loans in the pool come from California, 10% from Florida, 5% from Ohio, 3% from Michigan, and 2% from New York, the top 5 state shares are reported as "CA 25%", "FL 10%", "OH 5%", "MI 3%", and "NY 2%". We do not know how the loans in a group are divided among the remaining 45 states. From the top 5 state shares, we construct the shares of the most prevalent top 5 states in the ABS market (California, Florida, New York, Illinois, and Texas). On average, 30% of the loans in a pool come from California, 9% from Florida, 4% from New York, 3% from Illinois, and 2% from Texas. The results using the shares from the top 10 states were quite similar.

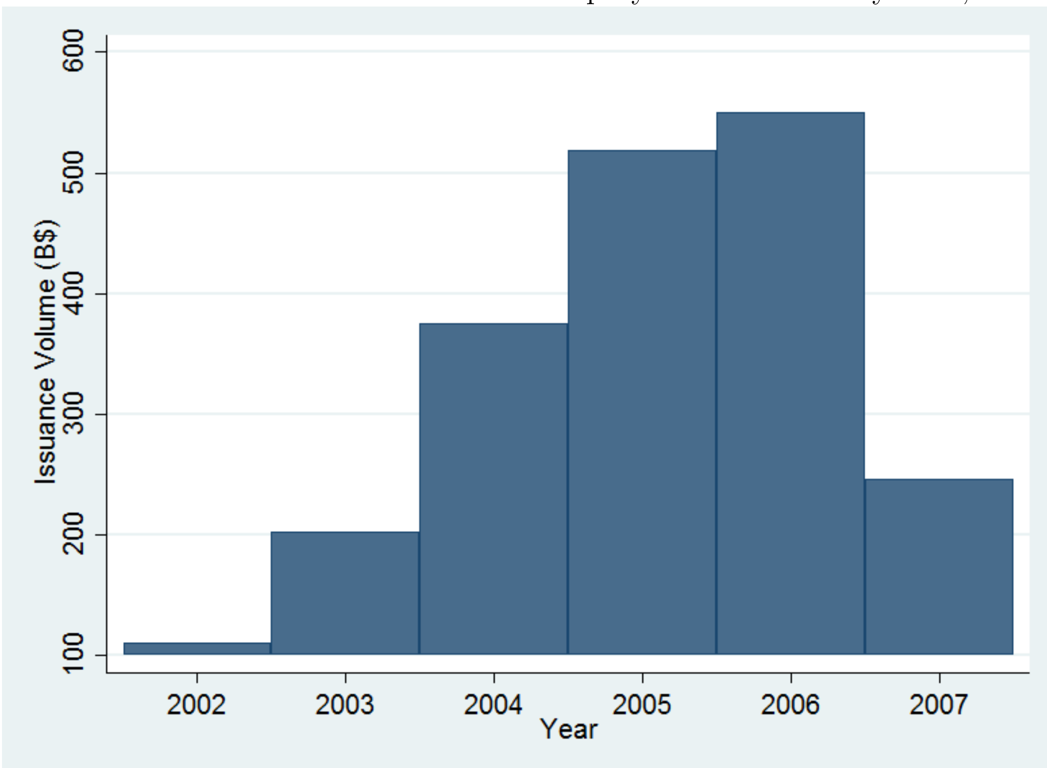
We have detailed information on the measured *ex ante* quality of the collateral for less than half of the securities. Nevertheless, all of our results are quantitatively and qualitatively similar when we control for these observable collateral characteristics. The weighted average loan-to-value (LTV) of the loans in a group has an average of 80% and a standard deviation of 6%. The average share of loans in a pool that are low or no documentation is 35% with some loan groups having no reduced documentation loans and some loan groups consisting entirely of reduced documentation loans. The weighted average maturity (WAM) of the mortgages is 353 months on average and ranges from 197 to 477 months. Bloomberg has two variables that contain summary information about the principal balances of the underlying

[14]As of May 2011, the Financial Industry Regulatory Authority (FINRA) requires reporting of all MBS transactions. FINRA released the data from 2011 onwards early to three groups of researchers; see Atanasov and Merrick (2013), Bessembinder, Maxwell, and Venkataraman (2013), and Hollifield, Neklyudov, and Spatt (forthcoming). Bloomberg contains modeled prices for many securities but average transactions prices for far fewer securities.

loans. These variables are the share of loans with original principal balances under $300,000 and the share of loans with original principal balances of $300,000 to $600,000.

For robustness, we consider whether our results are driven by the presence of the GSEs in the ABS market. Although none of our securities are issued by the GSEs, the GSEs bought substantial quantities of AAA ABS. Often, one loan group in a multiple loan group deal is tailored for one of the GSEs. The GSEs invested in AAA ABS backed by loan groups that consisted entirely of loans with principal balances that conform to their conforming loan limit. We can frequently identify such cases from the collateral group description Bloomberg provides. We create a variable called *conforming* that takes a value of 1 if the collateral group description contains terms such as "CONF", "CON", or "CONFORMING". The variable *conforming* takes a value of 0 if the collateral group description contains terms such as "NCONF", "NCON", or "NONCONFORMING". We manually code the exact collateral descriptions as conforming to prevent misclassification. If the collateral group description does not indicate whether the loans are conforming or non-conforming, *conforming* is missing.

FIGURE A.1. US Private-Label Home Equity ABS Issuance by Year, 2002-2007



Includes all deals with detailed data available via Bloomberg terminals for which detailed cashflows are available.

TABLE A.1. Summary Statistics

Variable	Unique Obs.	Mean	Std. Dev.	Min.	Max.
Panel A: Other Deal-Level Characteristics					
loangroups_2	1,299	0.61	0.49	0	1
loangroups3ormore	1,299	0.13	0.34	0	1
dealsize ($M)	1,299	980	587	90	4,928
crosscollat	1,299	0.34	0.47	0	1
excessspread (%)	1,277	3.8	1.6	0.0	10.9
leadtot ($M)	1,299	29,724	18,295	220	75,265
ResidgotCFs	1,181	0.27	0.44	0	1
Panel B: Other Security-Level Characteristics					
AAA	15,923	0.35	0.48	0	1
AA	15,923	0.23	0.42	0	1
A	15,923	0.21	0.41	0	1
BBB	15,923	0.20	0.40	0	1
subordination	15,242	12	8	0	98
spread	15,595	86	85	3	625
disagreetranche	15,923	0.26	0.44	0	1
Panel C: Group-Level Loan Characteristics					
conforming	972	0.52	0.50	0	1
foreclosurerate	2,274	16	7	0	52
fico	1,481	628	28	470	746
ltv	2,172	80	6	0.8	102
ownodocshare	1,552	35	24	0	100
top5geoshare	2,287	58	12	28	100
Cashare	2,287	30	16	0	100
Txshare	2,287	2	3	0	23
Nyshare	2,287	4	5	0	30
Flshare	2,287	9	5	0	31
Ilshare	2,287	3	4	0	18
balunder300kshare	2,257	64	23	0	100
bal300600kshare	2,257	31	19	0	100
balover600kshare	2,257	5	7	0	65
wam	2,325	353	16	197	477
collatlossshare	1,063	0.18	0.12	0.01	0.63

Notes: 1) The variable definitions are as follows. *nloangroups2* equals 1 if the number of loan groups is exactly 2, 0 otherwise; *nloangroups3ormore* equals 1 if the number of loan groups is 3 or more, 0 otherwise; *crosscollat* is a dummy variable that takes a value of 1 if the deal provides for some cross-collateralization across loan groups; *excessspread* is the excess coupon the collateral pays relative to what is owed on the securities; *leadtot* is the volume of ABS deals in that year by the lead manager; *ResidgotCFs* takes a value of one if the residual tranches in the deal received any cashflows, 0 otherwise; *subordination* is the % subordination the security has; *spread* is the coupon the security pays above one month LIBOR measured in basis points; *disagreetranche* takes a value of 1 if the ratings agencies disagree on the rating of that security; *conforming* takes a value of 1 if the description of the collateral group specifically refers to the loan group being conforming and takes a value of 0 if the description of the collateral group specifically states that the loan group is non-conforming; *foreclosurerate* is the foreclosure rate on the loan pool (in %); *fico* is the average FICO score of the loans at origination; *ltv* is the average loan-to-value (LTV) of the loans at origination (in %); *lownodocshare* is the fraction of loans that are No or Low documentation (in %); *top5geoshare* is the fraction of loans that are in the 5 most common states for that pool (in %); *Cashare*, *Flshare*, *Nyshare*, *Ilshare*, and *Txshare* is the sum of the share of loans (in %) from the most common 5 states in that deal that are in California, Florida, New York, Illinois, and Texas, respectively; *balunder300kshare* is the fraction of loans with original principal balances of under $300,000 (in %); *bal300600kshare* is the fraction of loans with original principal balances of $300,000 to $600,000 (in %); *balover600kshare* is the fraction of loans with original principal balances of $600,000 (in %); *wam* is the original weighted average maturity of the loans in months; *collatlossshare* is the fraction of the collateral value lost by Fall 2016. 2) The sample is all USD-denominated private-label ABS deals backed by US collateral issued 2002-2007 for which detailed cashflow information is available via Bloomberg.

TABLE A.2. Security Spreads and Security Complexity, AAA Securities Only

Dep. Var.	(1) *spread (bp)*	(2) *spread (bp)*	(3) *spread (bp)*	(4) *spread (bp)*	(5) *spread (bp)*	(6) *spread (bp)*	(7) *spread (bp)*
nloangroups	0.86*						
	(0.44)						
ntranches		0.066					
		(0.067)					
pagesmpool			-0.033**				
			(0.016)				
pageswaterfall				0.019			
				(0.039)			
nglossaryterms					0.0029		
					(0.0059)		
filesizemb						-0.074	
						(0.081)	
complexityindex							0.31
							(0.40)
dealsize	-0.0017***	-0.0015***	-0.0012**	-0.0015***	-0.0014***	-0.0014***	-0.0015***
	(0.00049)	(0.00047)	(0.00047)	(0.00047)	(0.00044)	(0.00044)	(0.00050)
crosscollat	0.85	1.10	1.48*	1.31*	1.09	1.24	1.13
	(0.80)	(0.80)	(0.80)	(0.77)	(0.88)	(0.77)	(0.87)
excessspread	-1.15***	-0.99***	-0.85***	-0.94***	-0.92***	-0.89***	-1.00***
	(0.30)	(0.27)	(0.24)	(0.25)	(0.26)	(0.24)	(0.29)
leadtot	0.000032*	0.000031*	0.000033**	0.000034**	0.000029*	0.000032*	0.000032**
	(0.000016)	(0.000016)	(0.000016)	(0.000016)	(0.000016)	(0.000016)	(0.000016)
subordination	0.19**	0.18*	0.17*	0.18*	0.18*	0.18*	0.19*
	(0.097)	(0.095)	(0.095)	(0.095)	(0.097)	(0.095)	(0.097)
disagreetranche	14.2***	14.2***	14.2***	14.2***	14.3***	14.2***	14.3***
	(2.72)	(2.72)	(2.70)	(2.71)	(2.77)	(2.72)	(2.79)
Constant	39.6***	39.6***	40.2***	39.5***	39.4***	39.7***	40.3***
	(2.44)	(2.42)	(2.42)	(2.52)	(2.42)	(2.42)	(2.60)
Observations	4,944	4,944	4,911	4,911	4,908	4,944	4,870
R^2	0.22	0.22	0.22	0.22	0.21	0.22	0.21
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top 5 State Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Entries shown are coefficients from a regression of the spread of the security, in basis points, relative to one month LIBOR on the variables shown. 2) See the appendix for variable definitions. 3) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 4) The unit of observation is a security. 5) Standard errors are clustered by deal.