Complexity in Structured Finance*

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Abstract

We study complexity in the market for securitized products, a market at the heart of the financial crisis of 2007-2009. Our measures of the complexity of these products rose substantially in the years preceding the financial crisis. We find that securities in more complex deals default more and have lower realized returns. The worse performance 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. Our results indicate that complexity obfuscates security quality.

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1. Introduction

Mortgage-backed securities (MBS) were at the heart of the recent financial crisis. While several real factors contributed to the subsequent recession, and the growth in mortgage credit was not confined to the subprime sector (Adelino, Schoar, and Severino (2016) and Foote, Loewenstein, and Willen (2016)), the financial crisis originated in subprime securities. The overwhelming majority of subprime mortgages were securitized and the issuance of complex subprime securities increased rapidly in the years preceding the crisis, possibly in response to increased demand for safe securities.[1] Most investors in the MBS market are institutions, rather than unsophisticated retail clients. Nevertheless, the majority of these securities defaulted, including more than 40% of securities rated AAA at issuance, and investors in investment-grade tranches rated below AAA often experienced negative realized returns.

Subprime securities are complex insofar as their creation involves the pooling of assets and tranching the cash flows from this collateral. Pooling both reduces information asymmetries (Riddiough (1997) and DeMarzo (2005)) and reduces risk through diversification (DeMarzo (2005) and Gennaioli, Shleifer, and Vishny (2013)). Another key feature of subprime MBS is the creation of multiple classes of securities backed by the same collateral. By creating multiple securities collateralized by the same assets, issuers can create informationally insensitive securities (Gorton and Pennacchi (1990) and Boot and Thakor (1993)). While prices are relatively easy for investors to observe, the structure and quality of the product are not given the extensive pooling and tranching in the MBS market. In particular, the structures of these securities are detailed in lengthy prospectuses, many of them hundreds of pages long, describing the collateral, the allocation of cash flows from the pool of loans to

[1]Gorton, Lewellen, and Metrick (2012) note the declining share of government securities and the increasing share of securitization in the stock of safe securities in the years immediately prior to the financial crisis. A large literature (e.g., Caballero (2006), Bernanke, Bertaut, DeMarco, and Kamin (2011), Sunderam (2015), Krishnamurthy and Vissing-Jorgenson (2015), Caballero, Farhi, and Gourinchas (2016), and Caballero and Farhi (forthcoming)) has studied the shortage of safe assets prior to the financial crisis. In his survey of the literature on safe assets, Gorton (2017, p. 564) asserts that "[s]ecuritization has been driven by a shortage of long-term safe debt." Gennaioli, Shleifer, and Vishny (2013) offer a theory in which the main driver of securitization is the demand for safe assets.

the securities in various states of nature, the ratings of the securities, and other structural features. Because prospective investors must carefully examine each security to understand the payoffs, increases in the complexity of securities raise buyers' search costs.[2]

While observers agree that these products are complex, and the discussion of security complexity featured prominently in the 2011 Financial Crisis Inquiry Commission's Report as a plausible contributing factor to the financial crisis, to date there is no consensus as to the role of complexity in MBS. 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 (e.g., Gorton and Metrick (2013)), then complexity arises as a natural byproduct of structuring. Indeed, markets for sophisticated structured products have historically emerged as a way to disseminate high risk collateral. For example, the modern Commercial Mortgage-Backed Securities (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 markets (Lucas, Goodman, Fabozzi, and Manning (2007), p. 4). Under this view, which we term "Incidental Complexity", 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. Rather, complexity arises efficiently as a byproduct of the demand for safe securities.

A less sanguine view, which we term "Obfuscation", is that complexity in securitized products arises as a result of strategic decisions on the part of issuers. Greater complexity increases buyers' search costs and affects 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

[2]There is a large literature in economics on search models. Rogerson, Shimer, and Wright (2005) and Lagos, Rocheteau, and Wright (2017) 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 over-the-counter (OTC) financial markets specifically.

Wolitzky (2012)). A related idea is that of Gabaix and Laibson (2006) wherein sellers shroud attributes of the product in a way that affects its true cost after including "add-on" pricing. In these models, complexity is used to make it difficult to learn the quality-adjusted price of a product at the expense of buyers. These models focus on the difficulty of learning the price of a product 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 the case of MBS, the obfuscation may be of the collateral or of how the cash flows from the collateral are allocated across different securities backed by the same collateral.

In this paper, we distinguish between these two views of complexity by examining the empirical relations between security complexity, security default, yields, and internal rates of return (IRRs). We start by constructing six variables that proxy for the complexity of structured products that are designed to measure the informational demands MBS deals impose on investors and the intricacies in structure across deals. We also construct a summary measure of complexity – an index of complexity – that synthesizes the information available in our six individual variables. All but one of our measures of complexity increase over the 2002-2007 period.

We then use data from the private label MBS (PLMBS) market, a segment of the MBS market that includes most subprime MBS, to establish that more complex securities perform worse. A one standard deviation increase in the complexity index is associated with a three percentage point increase in the risk of default. We conclude that this finding is consistent with obfuscation. It is robust across a variety of specifications including controls for the lead underwriter of the deal. Following Chernenko (forthcoming), we also measure the IRRs of the securities and find that they are lower for more complex securities.

While we find some evidence of issuers using complexity to obfuscate low quality collateral, 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 relation between complexity and security performance. More importantly, controlling for collateral performance directly in our regressions does not eliminate 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 flows 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 investment-grade tranches with less protection when the adverse home price scenario occurred such that more of them defaulted. Owners of the residual tranches, very often the issuers (see, for example, Demiroglu and James (2012) and Begley and Purnanandam (2017)), benefitted from the diversion.

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 as compensation for assuming higher default risk, 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 securities and their lower realized returns, 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, did not fully process the information in elaborate securities. As such, they did not demand a risk premium to hold more complex securities that defaulted more often.

Our findings are important for understanding the boom and bust in subprime securities and in designing the structure of the mortgage market going forward. The results indicate that the complexity of subprime securities made it difficult for investors to understand exactly what they were buying. They also help to explain the collapse 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)) shows 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).

Our paper is related to a small but growing literature on security complexity. Carlin (2009) examines strategic price complexity theoretically in a retail setting. Carlin, Kogan, and Lowery (2013) look at the effects of complexity on trading in a laboratory setting. Célérier and Vallée (2017) study complexity in the market for European retail structured products. Furfine (2014) finds that *loans* in more complex 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 an asset's payoff structure but they had to wade through a myriad 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 not offer higher spreads. Our results are thus consistent with assets having higher quality-adjusted prices 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 reasons why MBS may be more or less complex. 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 explore heterogeneity in complexity across issuers. Section 8 concludes.

2. The Structure of MBS and Hypothesis Development

2.1. **The Structure of MBS.** The US residential MBS market can be divided into two main asset classes: 1) residential MBS issued by Government-Sponsored Enterprises (GSEs), like Fannie Mae or Freddie Mac, 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 (2017) 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 home equity ABS are usually large investment banks. For instance, in 2006, the peak of the home equity ABS market, the three largest 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 cash flows 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 home equity ABS securities are used as collateral for CDOs. As Coval, Jurek, and Stafford (2009) argue, CDOs are even more complex than home equity 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 home equity ABS in our dataset for three reasons. First, CDOs backed by residential MBS are a much smaller asset class. Second, getting data on these securities is far more challenging than gathering data on home equity ABS. Bloomberg rarely has cash flows 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 home equity ABS for us to understand, explain, and exploit.

Home equity 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 loans 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).

2.2. **Hypothesis Development.** There are two main reasons structured finance securities may be complex. The first possibility is that issuers use complexity to create safe securities from risky collateral. Given the growth in the demand for safe securities in the years immediately prior to the financial crisis, issuers may have merely been responding to the increased demand for safe securities. The riskiness of the underlying collateral made a high level of complexity necessary. In this view, which we term "Incidental Complexity", the multitude of securities in an MBS deal, and the associated elaborate nature of the rules allocating cash flows from the collateral to the various securities in a deal, are necessary to generate some claims that are safe. Similarly, the collateral pool assembled to create a securitization may be large and diverse because diversification reduces risk. However, a large and diverse collateral pool may increase complexity and thus the time it takes for potential investors to understand the deal. Relatedly, some additional complexity may result from creating securities tailored to particular investors' needs or taste (Allen and Gale (1988)). For example, some investors may want tranches with long durations while other prefer shorter duration securities.

The main prediction of Incidental Complexity is that we should observe complexity increasing in the *ex ante* riskiness of the collateral.

Hypothesis 1. *Incidental Complexity and Collateral Risk*
If complexity is necessary to create safe securities from risky collateral, complexity should be higher in deals that have observably higher risk ex ante.

Regardless of whether complexity arises to reduce informational asymmetries, to allow for diversification, or to cater to specific investor demands, Incidental Complexity is an efficient response to investor demands. It also offers the following additional predictions: First, while complexity may be correlated with the *ex ante* riskiness of the collateral, since lower quality collateral requires more engineering to create high quality securities, complexity should not be correlated with

(1) The performance of the securities,

(2) The *ex post* performance of the collateral after controlling for observable collateral characteristics.

Secondly, there should be no difference in the quality-adjusted price of more and less complex securities.

The other possibility is that complexity shrouds the true risks of these products. While shrouding has typically been seen as sellers making it difficult to learn a product's true price (e.g., Gabaix and Laibson (2006) and Ellison and Ellison (2009)), in MBS markets the price of a security is relatively easy to observe but sellers can use complexity to obscure the security's true quality. Under this theory, which we term "Obfuscation", issuers use complexity to extract value from investors in the higher-rated tranches (i.e., tranches that do not take initial losses). For issuers to successfully extract value by obfuscating, investors must for some reason not pay the search costs to fully understand the instruments they invest in. One explanation for MBS investors' not fully investigating the securities they invest in is that they underestimate, or neglect entirely (Gennaioli, Shleifer, and Vishny (2012)), the possibility of a widespread decline in home prices. Indeed, as late as 2006, subprime executives themselves did not expect that home prices would fall substantially (Cheng, Raina, and Xiong (2014)).[3]

There are two ways, which are not mutually exclusive, that issuers may use complexity to obfuscate. First, issuers may shroud the unobservable quality of the collateral. If issuers can sell securities backed by lower quality collateral at the same price as high quality collateral, it benefits issuers presuming that lower quality collateral is cheaper for the issuers to acquire. Secondly, complexity can obscure cash flow diversions to junior tranches that may be held by issuers themselves. For example, this diversion can arise because of special features

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

of PLMBS designed to release cash flows to junior tranches if the collateral performs well (Gorton (2009)). The predictions of obfuscation are as follows:

Hypothesis 2. *Complexity and Security Performance*
If complexity obfuscates either low quality collateral or cash flow diversion to the junior tranches, more complex securities should

(1) Perform worse (default more and/or have lower realized IRRs), and
(2) Offer investors ex ante yields that are the same or lower than those of less complex securities.

We can distinguish more precisely between the two ways issuers may use complexity to obfuscate as follows:

Hypothesis 3. *Complexity to Obfuscate Collateral Quality*
If complexity obfuscates low quality collateral, the collateral of more complex deals should perform worse after controlling for security characteristics observable at origination.

Hypothesis 4. *Complexity to Obfuscate Cash Flow Diversion*
If complexity obfuscates cash flow diversion,

(1) Securities from more complex deals should perform worse even after controlling for collateral performance, and
(2) Residual tranches should be more likely to get cash flows in more complex deals.

3. Patterns in Complexity

3.1. **Sample Construction.** We collected information on all PLMBS deals available on Bloomberg. Our sample starts in 2002 and ends in 2007 as the home equity ABS market was quite small until the 2000s and there was very little issuance of home equity ABS from 2008 onwards.[4] 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 one hundred billion USD in every year before 2002.

[4]Although there are a few home equity 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.

We restrict our attention to USD-denominated home equity ABS backed by US assets for which Bloomberg has information on cash flows because the data quality is much higher for these securities.Our sample includes roughly half the home equity 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 of our variables are measured at the time the deal was issued; the exceptions are security default, the foreclosure rate on the underlying collateral group, the collateral loss rate, and the IRR. Security default is a binary variable that takes a value of 1 if the security had defaulted by August 2013. The foreclosure rate and collateral loss on the loan group is also measured in August 2013. We also collect data on the cash flows to the underlying security in each month from issuance to April 2016. We use these cash flows to construct the IRRs.

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 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.

3.2. **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 cash flows 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 more complex rules for allocating the cash flows from the collateral to the securities as well as more state-contingent clauses. A well informed investor would need more time to understand what cash flows 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.

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.

The complexity index is normalized to have a standard deviation of one for ease of interpretation. To make it easier to see its time series pattern, we normalize *complexityindex* to have a mean of 0 in 2002 by subtracting the mean of *complexityindex* in 2002.[5]

3.3. **Complexity Empirically.** 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

[5]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 A.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.

filesizemb all grow steadily. The number of loan groups in each deal is, however, 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 home equity ABS deals that increase their complexity were invented or even diffused during the 2000s. For example, Riddiough and Thompson (2011) document the existence of sophisticated MBS in the US since at least the 1850s.

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 factor loadings on the individual complexity variables in the index are 30% *nloangroups*, 28% *ntranches*, 16% *pagesmpool*, 13% *pageswaterfall*, 11% *nglossaryterms*, and 1% *filesizemb*. The first principal component accounts for 38% of the variation in our individual complexity variables.

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. 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; none of the correlations between *filesizemb* and the other complexity variables exceed 15%.

Aside from its implications for security performance, Incidental Complexity predicts that complexity should be higher when the collateral is riskier (Hypothesis 1) *ex ante*. Although we lack detailed collateral characteristics for many of the deals in our sample, for a subset of deals for which we have data, we consider whether complexity is higher when the collateral is known to be riskier. Our three main measures of collateral risk are the average FICO score of borrowers in the deal (higher *dealfico* means lower risk), the average LTV of the loans (higher *dealltv* means higher risk), and the fraction of loans that are low or no documentation (higher *deallownodoc* means more risk).[6]

Table 2 shows that, in general, complexity does not increase as the collateral gets riskier. Most of the coefficients on our collateral risk characteristics are statistically insignificant. In the few instances in which a coefficient on a collateral characteristic is statistically significant, it is as likely to have the 'wrong' sign in the sense of the coefficient indicating that complexity increases as the collateral gets safer than the converse. Thus, the relation between complexity and collateral risk does not support the Incidental Complexity hypothesis. The size of the lead underwriter (*leadtot*) has a positive relation with most of our complexity measures. We now turn to the relation between complexity and security performance to more precisely distinguish between the two views of complexity.

4. Complexity and Security Performance

4.1. **Measures of 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. Since security default corresponds to any realized loss or a projected loss from the rating agencies, even if a security suffers only a 0.01% loss, it is classified as being in default. Thus the default rate on our securities is considerably higher than the foreclosure rate on the underlying collateral of 15%.

We also calculate a finer-level of security performance using the cash flows to each individual tranche when the cash flow data are available. To do so, we follow Chernenko

[6]The collateral characteristics are variables we take from Bloomberg terminals and come to us at the collateral group level. To get a deal-level measure of the collateral characteristic, we value-weight each collateral group in the deal by its dollar amount.

(forthcoming) in calculating a security's 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 cash flows for the months in between are the actual cash flows received by the security. We do not calculate the IRRs for securities with negative interim cash flows, that are interest or principal only, as well as those with very large outliers in a given cash flow. We winsorize the IRRs 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 A security has a positive IRR. The bottom 10% of AAA securities likely experienced losses since the IRR of AAA securities is only 1.3% at the 10th percentile. The bottom 25% of AA, A, and BBB securities have very negative IRRs indicating substantial losses. Across all ratings, however, the upper half of securities have positive IRRs.

4.2. **Security Default and Complexity.** For our regressions, 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 our first tests of whether securities from more complex deals perform worse (Part 1 of Hypothesis 2). The table presents marginal effects from estimating equation (1). Throughout the paper, we present marginal effects rather than coefficients from probit regressions to make economic interpretation easier. 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 to 9 of Table 4 present the effects of complexity when we combine our complexity variables. While our measures of complexity are not sufficiently refined to allow us to perfectly disentangle the complexity of the collateral from the complexity of the structuring, in Column 7 we include *pagesmpool* and *pageswaterfall* simultaneously. Arguably, *pagesmpool* is the complexity measure that best captures the complexity of the collateral while *pageswaterfall* is our best proxy for the complexity of the structuring. When included jointly, the coefficients on both variables remain statistically significant and have similar magnitude to when they are included alone. Thus, both the complexity of the collateral and the complexity of the structuring matter for security performance. While not dispositive, these results suggest that complexity both facilitates the direction of cash flows towards lower rated tranches (Hypothesis 4) and shrouds low quality collateral (Hypothesis 3). We return to more precise tests of these hypotheses in the next section.

In Column 8, we include all 6 measures of complexity simultaneously without regard to potential collinearity. Although the magnitudes of the effects decrease, *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 9, 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 simply 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.

4.3. **Realized Rates of Return and Complexity.** As discussed earlier, default is measured coarsely and relies somewhat on the CRAs. We therefore also test Hypothesis 2 using IRRs as the measure of performance. Table 5 shows the result of regressing the security's IRR on our individual complexity variables. The coefficients on all the complexity variables indicate that the relation between the IRRs and complexity is negative. They are 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 larger than the difference in moving from the median to the 75th percentile of the distribution of the IRRs as illustrated by the summary statistics in Table 3.

4.4. **Security Performance Controlling for Collateral Performance.** The results so far support the view that, rather than being a byproduct of creating safe securities from risky collateral, the Incidental Complexity hypothesis, complexity obfuscates either collateral quality or cash flow diversion (Hypothesis 2). In Table 6, we take our first step to identify the nature of the obfuscation by controlling for the performance of the underlying collateral. According to Hypothesis 4, if complexity obfuscates cash flow diversion, we should observe a negative relation between our complexity variables and security performance even after controlling for the the quality of the collateral *ex post*. In Column 2 of Table 6, we therefore estimate equation (1) including *foreclosurerate* as a control variable while Column 3 controls for *collatlossshare*.[7]

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 of the positive 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). We obtain broadly similar results when we use the IRR as our measure of security performance; the results are in an appendix available upon request. The coefficients on our complexity variables drop by somewhat more in the IRR regressions than in the default probits, although they are still positive and usually statistically significant.

[7]For each tranche, we use the *foreclosurerate* and *collatlossshare* on the primary loan group serving as collateral for the tranches. We take the loan group the tranche is associated with directly from the Bloomberg API.

4.5. **AAA Securities and Performance.** 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 additional security is only 26 basis points. We also see larger increases in the risk of default for AAA securities from increases in *pagesmpool*, *pageswaterfall*, *nglossaryterms*, and *filesizemb*.

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. We also find that spreads predict IRRs for AAA securities. Our finding that spreads predict performance 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 yet been felt. Since we measure default much later (summer 2013) and IRRs in 2016, our performance measures 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.

While we also find that the AAA securities in more complex deals have lower IRRs, and that this relation is highly statistically significant, the magnitude of the coefficients on our complexity variables are actually smaller in the AAA sample than in the full sample. The results are available in an appendix. This finding is in contrast to the default sample. The main reason for the difference in results between the different performance measures is that our default measure captures in large part a prediction of the rating agencies as of summer 2013 while, as of spring 2016, relatively few of the AAA securities had actually suffered substantial losses (see Table 3). Given how well the economy performed between summer 2013 and spring 2016, some of the losses anticipated by the rating agencies did not eat through all of the investment-grade tranches below AAA such that the AAA tranches were less affected by complexity than the other investment-grade tranches.

4.6. **Sensitivity Analysis.** We subject our results to several sensitivity analyses with respect 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 9 of Table 4).

Column 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 mortgages, 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 backed by conforming pools (see Ghent, Hernández-Murillo, and Owyang (2015) and Adelino, Frame, and Gerardi (2017)). Thus deals in which the GSEs bought a security might have almost mechanically had one more loan group which might in turn have increased measured complexity along other dimensions. A 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 relation between complexity and security performance arises 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 estimated effect 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 for this relation which are not mutually exclusive. First, issuers may use complexity to mask collateral that is lower in quality in ways that investors cannot observe (Hypothesis 3). 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 rate 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) result in the CMBS market. When we use *collatlossshare* as the dependent variable (Columns 3 and 4), the coefficient on *complexityindex* 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. 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, we return to the other possible reason we find that more complex securities perform worse: complexity facilitates the direction of cash flows to the residual tranches which the issuers themselves may own (Hypothesis 4). In particular, 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 home 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 cash flows in the early years of a deal, thereby denying senior securities protection and increasing their subsequent default likelihood.

To test the second prediction of Hypothesis 4, we first construct a deal-level variable, *ResidgotCFs* that takes a value of one if a residual tranche in the deal receives any cash flows. In approximately 27% of the deals in our sample, the residuals received cash flows. 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 cash flows, a security is 3 percentage points more likely to default. In the AAA sample, a residual tranche receiving cash flow increases the risk of default by 9 percentage points (21%). We do not find a statistically significant relation between IRRs and the residuals getting cash flows, however.

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.[8]

To understand this mechanism, it is useful to consider the "XS/OC" structures that were typical in subprime securitizations.[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

[8]We also find that the relation between deal complexity and residuals getting cash flows holds for our individual complexity variables; the results are in an appendix available upon request.

[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. See Gorton (2009) for additional discussion.

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 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

We have demonstrated that more complex securities perform worse and found support for two possible mechanisms. However, for issuers to benefit from using complexity to shroud low quality collateral or to receive a larger share of the collateral's cash flows, it must also be the case that investors are not fully aware of the obfuscation. That is, investors must not fully price the worse performance of more complex securities. This is the second part of Hypothesis 2.

We thus 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, offered higher yields at issuance.

[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.

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 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. Who Issues Complex Securities?

Figure 2 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 each 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 of Table 12 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 a product's price, 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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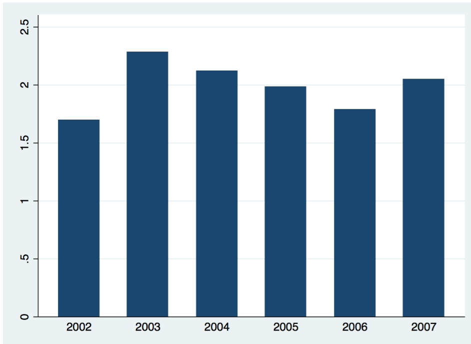
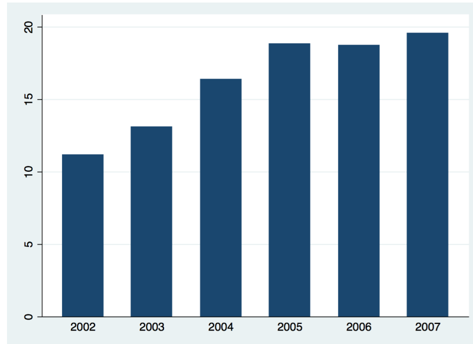
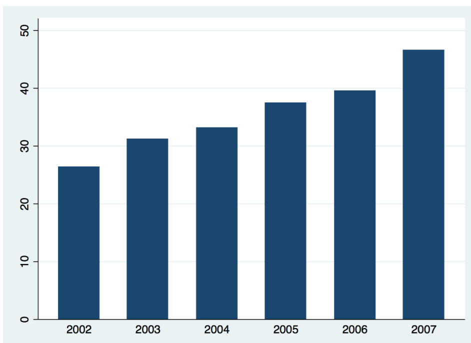
FIGURE 1. Means of Complexity Variables by Year, 2002-2007



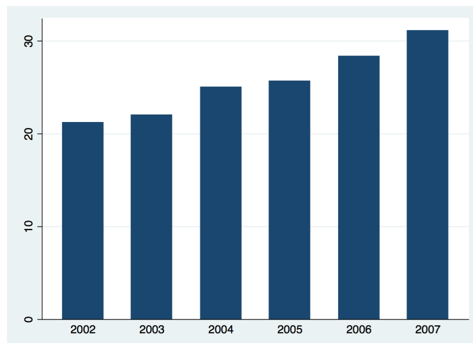
(a) No. of Loan Groups



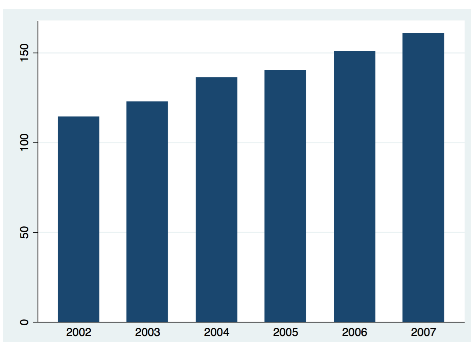
(b) No. of Securities



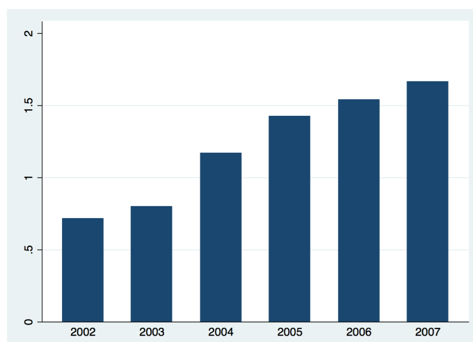
(c) No. of Pages Describing Collateral



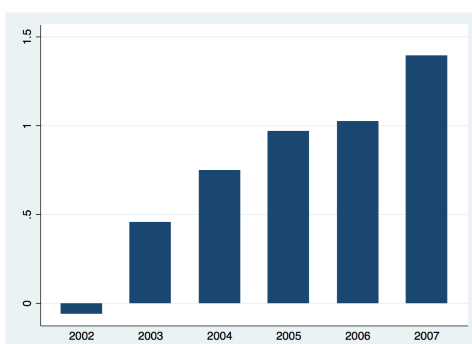
(d) No. of Pages Describing Waterfall



(e) No. of Terms in Glossary

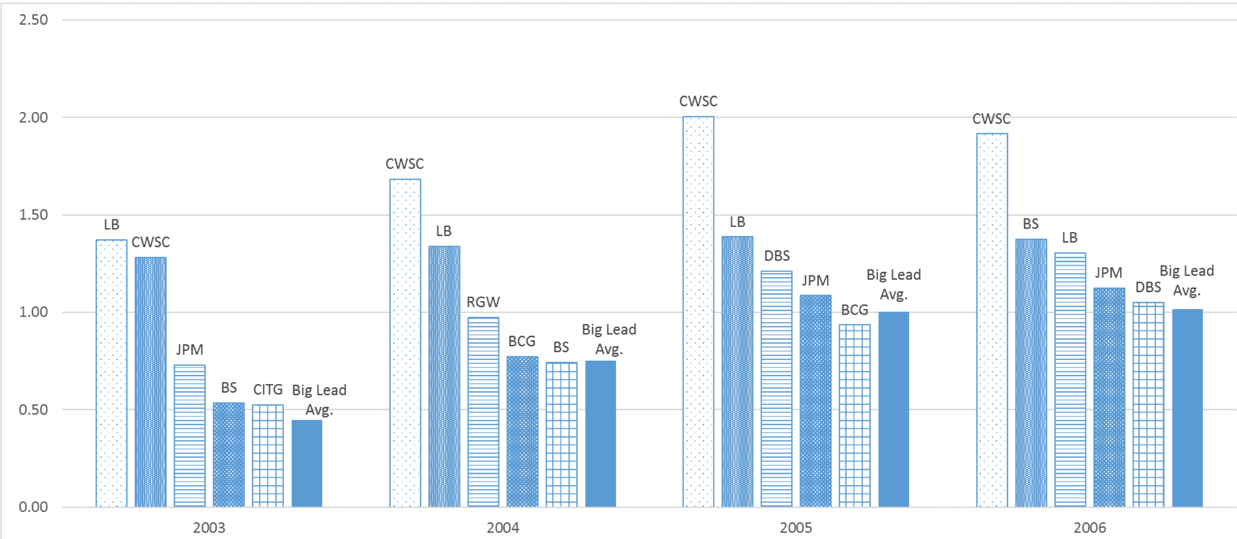


(f) File Size of Prosup (MB)



(g) Complexity Index

FIGURE 2. Complexity Index for Most Complex Issuers, 2003-2006



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 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. Complexity and *ex ante* Collateral Risk

Dep. Var.	(1) *nloangroups*	(2) *ntranches*	(3) *pagesmpool*	(4) *pageswaterfall*	(5) *nglossaryterms*	(6) *filesizemb*	(7) *complexityindex*
dealfico	0.00040	0.0092	-0.014	-0.034**	-0.23**	-0.00093	-0.0013
	(0.0015)	(0.0075)	(0.026)	(0.014)	(0.10)	(0.0027)	(0.0015)
dealltv	-0.0068	0.0081	-0.13	0.067	-0.73*	0.0010	-0.0054
	(0.0054)	(0.028)	(0.095)	(0.054)	(0.38)	(0.010)	(0.0055)
deallownodoc	-0.0021	-0.027***	0.0040	0.0090	-0.18	0.0021	-0.0030*
	(0.0017)	(0.0089)	(0.030)	(0.017)	(0.12)	(0.0032)	(0.0018)
leadtot	5.8e-06**	0.000022*	0.00011***	-0.000039	0.0018***	-5.3e-07	9.4e-06***
	(2.4e-06)	(0.000012)	(0.000042)	(0.000024)	(0.00017)	(4.5e-06)	(2.5e-06)
Constant	2.05**	7.06	46.4***	39.8***	315***	1.24	1.40
	(0.92)	(4.76)	(16.2)	(9.16)	(64.5)	(1.74)	(0.95)
Observations	668	668	664	665	663	668	658
R^2	5.5%	8.7%	7.0%	6.3%	19.4%	2.3%	8.0%
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Entries shown are coefficients from OLS regrssion of complexity variable on variables shown. 2) $dealfico$, *dealltv*, and *deallownodoc* are the average FICO, average LTV, and the share of low and no documentation loans in the deal. 3) Collateral characteristics are weighted by size of collateral group in the deal. 4) *leadtot* is the volume of Home Equity ABS deals in that year by the lead manager. 5) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 6) The unit of observation is a deal.

TABLE 3. Summary Statistics on Security Performance

Variable	Obs	Mean	Std. Dev.	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	12,537	-12.9	31.8	-76.2	-3.2	2.3	4.2	5.5
AAA_IRR	5,452	3.3	5.8	1.3	1.8	3.3	4.9	7.1
AA_IRR	2,867	-21.1	35.9	-83.5	-57.2	1.9	2.6	3.4
A_IRR	2,169	-26.9	38.2	-86.5	-67.3	1.6	3.9	4.8
BBB_IRR	2,049	-29.6	38.3	-86.7	-70.7	-5.6	4.4	6.1

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

Dep. Var.	(1) *default*	(2) *default*	(3) *default*	(4) *default*	(5) *default*	(6) *default*	(7) *default*	(8) *default*	(9) *default*
nloangroups	0.027***							0.019***	
	(0.0055)							(0.0064)	
ntranches		0.0026***						0.00045	
		(0.00097)						(0.0011)	
pagesmpool			0.00073***				0.00070***	0.00039*	
			(0.00020)				(0.00020)	(0.00022)	
pageswaterfall				0.00100***			0.00088**	0.00044	
				(0.00038)			(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***	0.000027***	0.000021***	0.000019***
	(6.1e-06)	(6.8e-06)	(6.1e-06)	(6.1e-06)	(5.8e-06)	(6.1e-06)	(6.1e-06)	(6.2e-06)	(6.1e-06)
crosscollat	-0.020***	-0.014**	-0.014**	-0.0097	-0.021***	-0.010	-0.013*	-0.031***	-0.026***
	(0.0071)	(0.0070)	(0.0069)	(0.0068)	(0.0070)	(0.0069)	(0.0069)	(0.0072)	(0.0070)
excessspread	-0.00071	0.0028	0.0048*	0.0037	0.0036	0.0061**	0.0032	-0.0038	-0.0044
	(0.0032)	(0.0031)	(0.0027)	(0.0029)	(0.0027)	(0.0027)	(0.0028)	(0.0032)	(0.0032)
leadtot	1.0e-07	1.0e-07	8.8e-08	2.2e-07	-3.3e-07	1.6e-07	1.7e-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)	(2.1e-07)	(2.2e-07)	(2.0e-07)
subordination	-0.0066***	-0.0070***	-0.0067***	-0.0069***	-0.0066***	-0.0068***	-0.0068***	-0.0064***	-0.0066***
	(0.00079)	(0.00082)	(0.00078)	(0.00081)	(0.00080)	(0.00082)	(0.00078)	(0.00077)	(0.00076)
spread	0.00027***	0.00028***	0.00031***	0.00031***	0.00025**	0.00027***	0.00031***	0.00028***	0.00030***
	(0.00011)	(0.00011)	(0.00010)	(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***	0.052***	0.054***	0.053***
	(0.010)	(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	14,467	14,357	14,357
Std. Errors Clustered by Deal	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating at Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top 5 State Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.52	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)	(9)
Dep. Var.	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*
nloangroups	-1.04*							0.73	
	(0.55)							(0.71)	
ntranches		-0.29**						-0.27**	
		(0.11)						(0.13)	
pagesmpool			-0.052**				-0.048*	-0.059**	
			(0.025)				(0.025)	(0.028)	
pageswaterfall				-0.11**			-0.11**	-0.072	
				(0.051)			(0.050)	(0.054)	
nglossaryterms					-0.021***			-0.020***	
					(0.0059)			(0.0060)	
filesizemb						-0.13		-0.055	
						(0.28)		(0.24)	
complexityindex									-2.34***
									(0.58)
dealsize	-0.0017***	-0.0015**	-0.0018***	-0.0018***	-0.0019***	-0.0021***	-0.0015**	-0.0011*	-0.0010
	(0.00058)	(0.00061)	(0.00062)	(0.00062)	(0.00058)	(0.00057)	(0.00063)	(0.00065)	(0.00064)
crosscollat	0.18	0.28	-0.078	-0.37	0.56	-0.24	-0.19	0.85	0.74
	(0.82)	(0.83)	(0.79)	(0.78)	(0.78)	(0.78)	(0.79)	(0.86)	(0.84)
excessspread	0.34	0.49	0.12	0.28	0.25	0.060	0.33	0.66*	0.79**
	(0.34)	(0.33)	(0.30)	(0.33)	(0.31)	(0.30)	(0.32)	(0.37)	(0.36)
leadtot	0.000033	0.000033	0.000034	0.000021	0.000063**	0.000032	0.000025	0.000057*	0.000040
	(0.000028)	(0.000028)	(0.000028)	(0.000029)	(0.000029)	(0.000028)	(0.000029)	(0.000030)	(0.000029)
subordination	0.73***	0.75***	0.74***	0.75***	0.72***	0.75***	0.74***	0.73***	0.72***
	(0.14)	(0.15)	(0.15)	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)
spread	0.068***	0.068***	0.067***	0.067***	0.066***	0.068***	0.067***	0.065***	0.066***
	(0.0100)	(0.0100)	(0.010)	(0.0100)	(0.0100)	(0.0100)	(0.0100)	(0.0100)	(0.010)
disagreetranche	-5.11***	-4.98***	-4.91***	-5.01***	-5.37***	-5.03***	-4.94***	-5.11***	-5.11***
	(1.29)	(1.28)	(1.29)	(1.28)	(1.28)	(1.28)	(1.28)	(1.29)	(1.29)
Constant	-26.1***	-25.5***	-25.2***	-24.5***	-24.5***	-25.7***	-24.0***	-22.6***	-30.7***
	(3.37)	(3.39)	(3.41)	(3.40)	(3.41)	(3.38)	(3.41)	(3.47)	(3.59)
Observations	11,419	11,419	11,343	11,350	11,382	11,419	11,337	11,300	11,300
R^2	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
Std. Errors Clustered by Deal	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating at Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top 5 State Shares	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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			0.0074***			0.0072***
			(0.00075)			(0.0010)
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^2	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 Cash Flows 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) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 3) The unit of observation in Columns 1 and 2 is a security. 4) Standard errors in Columns 1 and 2 are clustered by deal. 5) 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. 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. We selected our sample as follows. We first downloaded the names of all non-prime MBS deals (non-CDO and non-jumbo) issued from 1993 through 2013 for which cash flows are available on Bloomberg. We could not obtain prospectus supplments for most of the deals from the early years of the sample. Thus, from that sample of 2,630 deals, we drop 290 deals issued before 2002 or after 2007 since we do not have enough deals prior to 2002 or after 2007 to control for temporal heterogeneity. Of the remaining 2340 deals, we were able to get prospectus supplements for 1508 deals. We were unable to obtain tranche-level data for an additional 2 deals and 7 deals were actually agency deals that had been misclassified. Of the remaining 1499 deals, the tranche and collateral-level data did not provide enough information to calculate the excess spread for 7 deals leaving us with a sample of 1492 deals. Of these 1492 deals, 193 deals contained only collateral groups that included fixed-rate mortgages. We drop all tranches backed by fixed-rate collateral such that our final sample includes 1299 deals.

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.[11]

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"

We then define the deal-level variable *ResidgotCFs* as equal to one if any residual in the deal received cash flows 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

[11]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.

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.[12] 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%

[12]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.

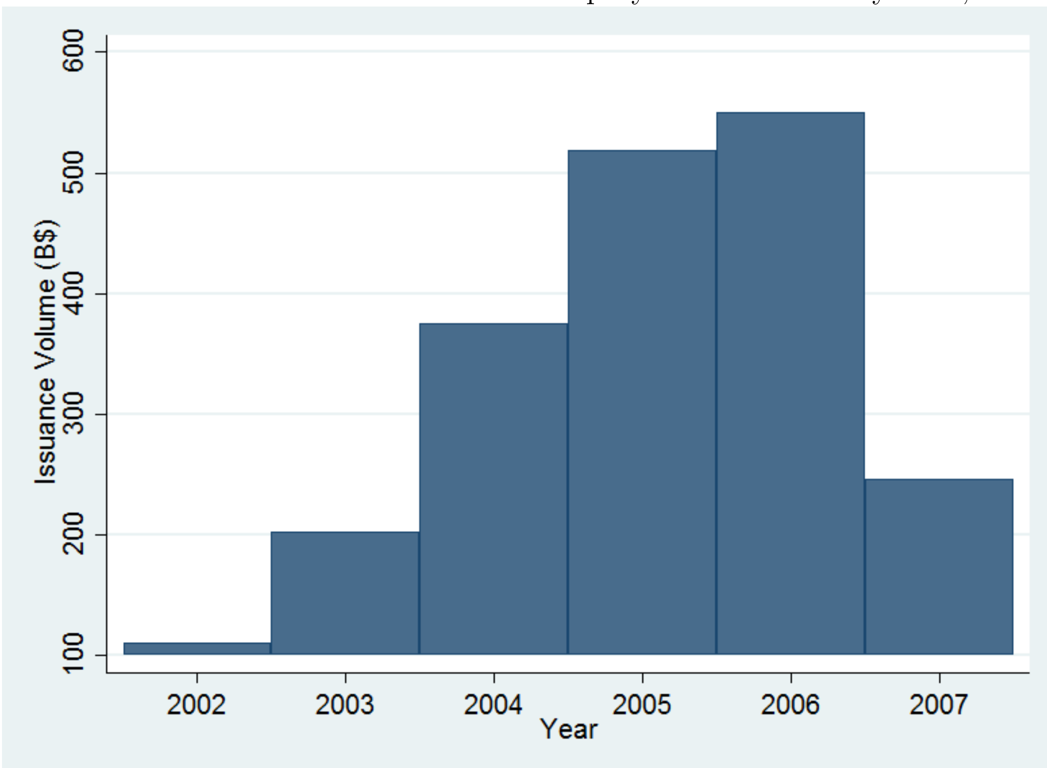
from Illinois, and 2% from Texas. The results using the shares from the top 10 states were quite similar.

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 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.

We have two measures of the performance of the collateral, *foreclosurerate* and *collatlossshare*. We download *foreclosurerate* directly from Bloomberg. *foreclosurerate* is the percent of loans in foreclosure such that it is not value-weighted. We construct *collatlossrate* as the total principal loss on the collateral divided by the original collateral value such that it is value-weighted.

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 cash flows 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 cash flows, 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 cash flow information is available via Bloomberg.

TABLE A.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.

A.2. **Additional Empirical Results.**

Table A.3. Realized Security Returns Controlling for Security Performance

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*
complexityindex	-2.33***	-2.09***	-1.26**	-2.30***	-2.07***	-1.42
	(0.59)	(0.59)	(0.61)	(0.76)	(0.76)	(1.02)
foreclosurerate		-0.32***			-0.34***	
		(0.075)			(0.098)	
collatlossshare			-1.36***			-1.85***
			(0.13)			(0.20)
dealsize	-1.09*	-1.17*	-0.80	-0.46	-0.53	1.06
	(0.65)	(0.64)	(0.65)	(0.98)	(0.98)	(1.24)
crosscollat	0.74	0.98	0.60	-0.51	-0.45	-4.61***
	(0.85)	(0.84)	(0.97)	(1.18)	(1.17)	(1.72)
excessspread	73.5**	86.1**	86.9**	29.9	37.5	62.2
	(36.6)	(36.2)	(39.5)	(44.0)	(44.0)	(49.5)
leadtot	3.58	2.58	-1.42	6.13*	4.98	-3.89
	(2.88)	(2.86)	(3.17)	(3.47)	(3.46)	(4.51)
AAA Rated	45.8***	45.3***	46.4***	47.8***	47.6***	54.2***
	(2.90)	(2.94)	(4.33)	(4.70)	(4.76)	(7.05)
AA Rated	23.0***	22.7***	22.5***	20.7***	20.7***	21.5***
	(2.29)	(2.30)	(2.77)	(3.48)	(3.50)	(4.51)
A Rated	11.7***	11.6***	11.0***	8.31***	8.34***	7.68***
	(1.38)	(1.38)	(1.47)	(1.98)	(1.98)	(2.24)
subordination	71.4***	74.3***	100***	78.9***	79.6***	93.7**
	(14.0)	(14.5)	(28.1)	(22.0)	(22.7)	(41.2)
spread	6.41***	6.39***	6.80***	3.33**	3.37**	3.03**
	(1.01)	(1.01)	(1.12)	(1.40)	(1.41)	(1.30)
disagreetranche	-4.73***	-4.93***	-5.47***	-3.00*	-3.14*	-5.45***
	(1.30)	(1.29)	(1.24)	(1.72)	(1.71)	(1.60)
Constant	-30.4***	-29.1***	-27.0***	77.9**	89.4***	74.5**
	(3.64)	(3.66)	(4.20)	(30.5)	(31.0)	(31.9)
Observations	11,149	11,149	7,249	5,754	5,754	3,140
R^2	0.45	0.45	0.52	0.51	0.51	0.62
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

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

Table A.4. Complexity and Realized Returns on Securities, AAA Securities Only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*	*IRR*
nloangroups	-0.23**						0.025	
	(0.11)						(0.11)	
ntranches		-0.077***					-0.084***	
		(0.020)					(0.024)	
pagesmpool			-0.0052				-0.0046	
			(0.0033)				(0.0031)	
pageswaterfall				0.0054			0.012*	
				(0.0069)			(0.0073)	
nglossaryterms					-0.0011		-0.00038	
					(0.00082)		(0.00076)	
filesizemb						-0.048***	-0.037***	
						(0.017)	(0.014)	
complexityindex								-0.31***
								(0.096)
dealsize	-0.00019**	-0.00012	-0.00024***	-0.00029***	-0.00027***	-0.00027***	-0.00014	-0.00015
	(0.000092)	(0.000087)	(0.000091)	(0.000092)	(0.000082)	(0.000081)	(0.000095)	(0.000098)
crosscollat	-0.17	-0.12	-0.23*	-0.26**	-0.23*	-0.26**	-0.066	-0.12
	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.12)
excessspread	0.013	0.064	-0.049	-0.068	-0.042	-0.054	0.059	0.049
	(0.055)	(0.060)	(0.056)	(0.057)	(0.056)	(0.057)	(0.061)	(0.059)
leadtot	-0.000010***	-9.3e-06**	-0.000010**	-0.000010***	-8.5e-06**	-0.000011***	-7.3e-06*	-9.3e-06**
	(4.0e-06)	(3.8e-06)	(4.1e-06)	(3.8e-06)	(4.2e-06)	(4.0e-06)	(3.8e-06)	(4.0e-06)
subordination	0.094***	0.098***	0.097***	0.099***	0.097***	0.098***	0.098***	0.095***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
spread	-0.063***	-0.063***	-0.064***	-0.064***	-0.063***	-0.064***	-0.064***	-0.063***
	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0076)	(0.0075)
disagreetranche	-0.45*	-0.41	-0.42	-0.44	-0.46*	-0.43	-0.42	-0.43
	(0.26)	(0.26)	(0.27)	(0.27)	(0.26)	(0.27)	(0.26)	(0.26)
Constant	4.06***	4.11***	4.13***	4.01***	4.07***	4.09***	4.05***	3.39***
	(0.54)	(0.55)	(0.55)	(0.55)	(0.54)	(0.54)	(0.55)	(0.59)
Observations	4,897	4,897	4,864	4,864	4,881	4,897	4,843	4,843
R^2	0.29	0.30	0.29	0.29	0.29	0.29	0.30	0.30
Std. Errors Clustered by Deal	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

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

Table A.5. Complexity and Security Default after Controlling for Collateral Performance, AAA Securities Only

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*default*	*default*	*default*	*default*	*default*	*default*
complexityindex	0.079***	0.075***	0.095***	0.075***	0.068***	0.081***
	(0.012)	(0.011)	(0.015)	(0.016)	(0.015)	(0.021)
foreclosurerate		0.0051***			0.0063***	
		(0.0012)			(0.0017)	
collatlossshare			0.013***			0.017***
			(0.0017)			(0.0032)
dealsize	0.035**	0.036**	0.037**	0.017	0.019	0.059*
	(0.014)	(0.014)	(0.017)	(0.022)	(0.022)	(0.034)
crosscollat	-0.062***	-0.069***	-0.14***	-0.049**	-0.051**	-0.15*
	(0.016)	(0.016)	(0.023)	(0.023)	(0.023)	(0.077)
excessspread	-0.39	-0.60	-1.60*	0.51	0.43	-2.57**
	(0.69)	(0.69)	(0.89)	(0.91)	(0.91)	(1.11)
leadtot	0.021	0.038	0.11**	-0.068	-0.052	0.15
	(0.040)	(0.040)	(0.053)	(0.058)	(0.058)	(0.11)
subordination	-1.08***	-1.12***	-0.81***	-1.84***	-1.86***	-1.15**
	(0.18)	(0.19)	(0.22)	(0.26)	(0.26)	(0.46)
spread	0.69***	0.69***	0.75***	0.53***	0.53***	0.35*
	(0.12)	(0.12)	(0.20)	(0.14)	(0.14)	(0.20)
disagreetranche	0.024	0.028	0.075	0.050	0.059	0.14
	(0.045)	(0.044)	(0.070)	(0.064)	(0.063)	(0.089)
Observations	4,810	4,810	2,425	2,501	2,501	821
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	0.40	0.40	0.40	0.34	0.34	0.26

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 A.6. Residual Cash Flows and IRRs

	(1)	(2)	(3)
Dep. Var.	*IRR*	*IRR*	*ResidgotCFs*
ResidgotCFs	-0.65	0.081	
	(1.00)	(0.12)	
dealsize	-0.0021***	-0.00027***	0.000074***
	(0.00061)	(0.000087)	(0.000023)
crosscollat	-0.55	-0.23*	-0.32***
	(0.88)	(0.13)	(0.028)
excessspread	0.069	-0.068	-0.031***
	(0.32)	(0.061)	(0.011)
leadtot	0.000037	-0.000010**	-4.0e-06***
	(0.000029)	(4.0e-06)	(8.4e-07)
AAA Rated	45.1***		
	(3.08)		
AA Rated	22.7***		
	(2.36)		
A Rated	11.5***		
	(1.39)		
subordination	0.78***	0.098***	
	(0.16)	(0.017)	
spread	0.066***	-0.062***	
	(0.010)	(0.0074)	
disagreetranche	-5.22***	-0.44	
	(1.31)	(0.27)	
complexityindex			0.097***
			(0.017)
Constant	-25.8***	4.01***	
	(3.56)	(0.57)	
Observations	10,911	4,682	1,151
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
R^2	0.45	0.29	
Pseudo R^2			0.12

1) Entries shown in columns 1 and 2 are coefficients from OLS regressions of the dependent variable indicated on variables shown. 2) Entries shown in column 3 are marginal effects from probit estimation. 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 A.7. Residual Cash Flows and Deal Complexity: Individual Complexity Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*ResidgotCFs*	*ResidgotCFs*	*ResidgotCFs*	*ResidgotCFs*	*ResidgotCFs*	*ResidgotCFs*
nloangroups	0.076***					
	(0.016)					
ntranches		0.011***				
		(0.0031)				
pagesmpool			0.0019**			
			(0.00074)			
pageswaterfall				0.0082***		
				(0.0014)		
nglossaryterms					-0.00036*	
					(0.00020)	
filesizemb						0.021**
						(0.0085)
dealsize	0.000084***	0.000085***	0.00010***	0.000098***	0.00011***	0.00011***
	(0.000022)	(0.000022)	(0.000022)	(0.000022)	(0.000021)	(0.000021)
crosscollat	-0.31***	-0.29***	-0.28***	-0.27***	-0.25***	-0.27***
	(0.029)	(0.028)	(0.028)	(0.028)	(0.029)	(0.028)
excessspread	-0.023**	-0.017	-0.0055	-0.016	0.00025	-0.0016
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
leadtot	-3.5e-06***	-3.5e-06***	-3.5e-06***	-3.2e-06***	-2.8e-06***	-3.3e-06***
	(8.4e-07)	(8.3e-07)	(8.4e-07)	(8.5e-07)	(9.0e-07)	(8.4e-07)
Observations	1,164	1,164	1,159	1,159	1,159	1,164
Year of Issue FEs	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.11	0.10	0.10	0.11	0.09	0.10

1) Entries shown are marginal effects from probit estimation of the dependent variable indicated on variables shown. 2) ***, **, and * denote statistical significance at the 1, 5, and 10% levels. 3) The unit of observation is a deal.

TABLE A.8. Security Spreads and Security Complexity, AAA Securities Only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	*spread (bp)*	*spread (bp)*	*spread (bp)*	*spread (bp)*	*spread (bp)*	*spread (bp)*	*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.

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