Essays on auto loan asset-backed securities: Moral hazard along the securitization chain, and the cross section of expected returns

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Abstract

In the first chapter, I study prime US auto loan asset-backed securities (ABs) issued between 2002 and 2007, and investigate whether deals in which an investment bank securitizes loans acquired in whole-loan sales differ from deals where a lender securitizes collateral they have originated themselves. I argue that moral hazard issues arising from asymmetric information between agents involved in the securitization chain are stronger in deals of whole loans. In line with this view, I show that pool losses are larger in this case, controlling for observable risk characteristics, and conclude that moral hazard is operative in this market. Further, I find that rating agencies were able to recognize the greater risks of whole-loan deals and to adjust their assessments accordingly. Given ratings' important role in securitized debt markets, this implies that prices reflected incentive issues, thus mitigating possible negative effects on macroeconomic outcomes. Finally, I show that for lower-rated tranches, investors priced moral hazard beyond what is contained in ratings.

In the second chapter, I study how prices of auto loan ABS behave over the lifetime of the bonds. Asset-pricing theory posits that expected returns are determined by securities' systematic risk, which can be measured as exposure to risk factors. I employ an interest rate factor as well as different auto loan ABS market factors to study the cross section of expected monthly returns over the period December 1994 to April 2007. In Fama-MacBeth regressions, I find that the interest rate factor is significantly related to expected returns, and in univariate portfolio sorts I find that it generates a risk premium of 5 basis points per month. Furthermore, an auto loan ABS market factor that uses excess returns of lower-rated tranches over AAA-rated ones to measure systematic risk is also priced, with risk premia of 4 to 5 basis points. Finally, I study robustness of the results to the inclusion of time to maturity and credit ratings as alternative measures of risk, and find that exposure to the market factor is robustly priced, while the role of the interest rate factor is taken up by the additional covariates.

INDEX WORDS: Securitization; Auto loan ABS; Moral hazard; Asset pricing; Credit ratings; Betas

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Chapter 1

Moral hazard along the securitization chain of US auto loan ABS before the financial crisis

1.1 Introduction

The widespread adoption of securitization has been an important transformative force in the US and global financial systems over the last decades since the practice was pioneered in the 1970s. The pooling and structuring of cashflows radically changed the way many assets are financed, and for lenders provided new opportunities for capital management and access to liquidity. From the beginning, consumer credit such as mortgages and car loans have accounted for a large share of securitized assets. Securitization markets grew strongly throughout the 1990s and early 2000s, and the technique was hailed as enhancing risk sharing in the economy, and reducing financing costs for consumers and firms. However, the financial crisis that started in 2007 has led to a more sceptical view of structured finance. Securitization contributed to the expansion of subprime mortgage credit in the US in the years prior to the crisis, which was a driver of the rise in mortgage delinquencies that started after house prices peaked in 2006 and is regarded as a principal cause of the crisis ([58], [18]). In particular, the originate-to-distribute lending model, in which loan originators pass debt along the securitization chain to be ultimately structured into securities, created multiple points of asymmetric information and distorted incentives ([6], [8]). These are thought to have contributed to a decline in lending standards that led to the rise in subprime loans ([63]). In this paper, I use a dataset on US auto loan asset-backed securities (ABS) to investigate the consequences of informational frictions along the securitization chain. The first question I ask is whether longer securitization chains, and corresponding greater incentive problems, have a negative effect on the quality of securitized car loan pools.

I then investigate credit ratings of tranches of auto loan ABS deals backed by those loan pools. Ratings are important in structured finance since risk analysis is costly due to the complexity of securities, and investors are thus particularly inclined to base their decisions on rating agencies' assessments. Ratings were vital for the growth of securitization and for marketing securities to investors, a large share of which was rated triple-A, and whose investor base was significantly expanded by the availability of ratings. However, when the crisis hit, an unprecedented amount of structured finance securities was downgraded, including large numbers of formerly top-rated tranches. Many credit ratings are in retrospect widely viewed to have been overly optimistic, and agencies are blamed to have insufficiently taken into account risks to collateral quality. My second question pertains to ratings quality, asking whether credit ratings of auto loan ABS before the Financial Crisis reflected the severity of incentive problems along the securitization chain. Lastly, I turn to the pricing of securities. If investors understand the incentive problems and price tranches accordingly, then negative effects on real outcomes will be mitigated ([30], [11]). Given that ratings are the most important driver of spreads of securitized debt, prices will incorporate incentive problems at least to the extent that they are accounted for by rating agencies. A number of studies have found that investors in securitized debt do not exclusively rely on ratings for their decisions, especially for tranches rated below triple-A ([2], [61], [35]). My third question thus asks whether tranche prices reflect moral hazard between the agents involved in the transaction beyond what is included in ratings.

At the core of my approach is the comparison between auto loan ABS deals in which loans are securitized by their originator (originator deals) and deals in which an investment bank securitizes loans they previously acquired from loan originators (whole-loan deals). For two reasons, problems stemming from asymmetric information between agents involved in the transaction are greater in whole-loan deals. First, originators' incentives are different in the two cases. Second, while in originator deals there is asymmetric information only between loan originators and investors in tranches, in whole-loan deals informational frictions arise both between originators and the securitizing investment bank, as well as between the latter and investors. Loan originators have private information along a number of dimensions about portfolios they securitize or sell. They choose the intensity of ex-ante screening of borrowers, and of ex-post monitoring if they keep servicing the loans, both of which are not observable by other agents. Furthermore, originators know how the receivables being sold were chosen from their overall portfolio. As a result, an originator faces moral hazard, since they can reduce the screening or monitoring intensity or adversely select worse loans, all of which lower the value to counterparties. Crucially for my empirical approach, while this applies to both the situation when an originator securitizes loans and when they sell them, the moral hazard issue is stronger in the latter case. This is due to the fact that an originator who securitizes part of their portfolio maintains a stake in the loans, while in a whole-loan sale the seller does not keep a direct interest in cashflows from the loans. Regarding the second friction, investment banks that securitize acquired car loans generally choose the pool from a larger portfolio of loans that they own. While buyers of whole loans lack some of the knowledge that originators have, they nonetheless possess superior information compared to investors in tranches, which creates another moral hazard problem. As a consequence of these considerations, I expect loan quality to be higher in pools securitized by their originator, controlling for observable risk characteristics.

I study the effect of a longer securitization chain on loan quality by comparing the performance of loan pools underlying the two types of deals. My sample includes auto loan ABS deals issued in the US from 2002 to 2007. While whole-loan securitizations are less common for car loans than they are for mortgages, there were 17 such transactions completed in the US before the financial crisis, which amounts to about 9 percent of all prime auto loan securitizations during that period. I test for the effect of worse incentives in whole-loan deals by regressing final losses of pools on a dummy for such deals, controlling for other determinants of collateral losses. My results show that losses on pools from whole-loan deals are about 0.4 percentage points higher than on pools securitized by their originator, and the difference is statistically significant. This effect is economically meaningful in relation to the average loss rate of deals in my sample of 1.35 percent. A longer securitization chain and associated aggravated incentive problems thus lead to worse collateral quality.

I then turn to the issue of whether lower collateral quality caused by moral hazard is reflected in credit ratings of tranches, where I employ two different approaches. The first are linear regressions of ratings converted to numerical values, which exclude securities carrying triple-A ratings to avoid truncation issues. Controlling for the two main determinants of tranches' credit risk, pool quality and credit enhancements, as well as for other factors rating agencies take into account, I find that ratings on tranches from whole-loan deals are significantly lower. The estimates imply that securities with the same observable characteristics receive ratings that are at least one notch worse if they are backed by whole-loan collateral. I qualitatively confirm this finding with the second approach, which consists in ordered logit regressions of letter rating classes, where I include the lowest-ranked triple-A rated tranche of each deal. For originator deal tranches, the odds of being in a given rating category or better are estimated to be 2.6 to 3.2 times larger. I conclude that rating agencies put a penalty on whole-loan collateral.

In my last tests I study if tranches from whole-loan deals price differently, controlling for credit ratings. The analysis is done separately for triple-A rated senior tranches and subordinated ones, to allow for the possibility that investors did due diligence of the latter ones, while for the former they relied on rating agencies' assessments. A number of studies have found that investors in structured finance securities look beyond ratings when pricing tranches, but this is mainly the case for subordinate tranches ([2], [61]). Senior securitization tranches are often regarded as informationally insensitive. In both cases, I run linear regressions of issuance spreads of individual securities. For tranches rated below triple-A, I find that, controlling for ratings with dummy variables, as well as for other pricing factors such as market conditions and liquidity, spreads are significantly larger on whole-loan tranchess, where my estimates of the effect vary between 19 and 33 bps. In particular, the results are not driven solely by securities rated rated below triple-B, which have much larger spreads. On the other hand, I find that for triple-A rated securities there is no difference in pricing between the two types of deals.

The experience of the financial crisis that started in 2007 has reinforced academic interest in securitization and credit ratings as two of the elements closely connected to the events. The paper that is most directly related to mine is [30], who study Alt-A mortgage-backed securities issued between 2003 and 2007. Like me, they find that collateral pools consisting of loans acquired previously in whole-loan sales perform worse. Consistent with the narrative that lower screening efforts are generating these results, they show that the effect is entirely driven by pools with a relatively high share of low-documentation mortgages. In those contracts, the lending decision heavily relies on borrowers' credit scores, and proof of income is waived ([51], [56]), thus giving more importance to soft information acquired through screening. This increases the degree of asymmetric information. In retail auto finance, the concept of low documentation loan does not exist, and proof of income is generally a stated requirement by lenders. Viewed in this way, my finding stands in contrast to [30] by showing that moral hazard leads to lower quality in loan pools with proof of income. However, a number of factors can help reconcile the results. One is the fact that, in general, the documentation required for a car loan is less than for a mortgage, e.g. a verified list of assets is not always required. Furthermore, it is not uncommon for auto lenders to do without income verification for borrowers with high credit scores. Lastly, the fact that I am studying prime auto loans whereas [30]'s sample is made up of Alt-A mortgages may be important. This is supported by the findings of [33], who investigates the role of asymmetric information between originators and investors in tranches in a similar setup, studying differences in quality between loans securitized and loans held on balance sheet. Using data on US mortgages originated in 2005 and 2006, he finds that privately securitized loans perform worse that ones kept by the lender, but this is only the case for prime loans. There is no such effect for subprime mortgages. Similarly, [5] find that originators select agency loans with high prepayment risk to sell to the GSEs, but detect no adverse selection for subprime loans. A possible explanation for these findings is that documentation levels in general may by lower for prime loans, creating more scope for problems arising from asymmetric information.

[30] also present results regarding differences in ratings between whole-loan and originator deals. They follow an inverse approach, testing whether different measures of credit enhancement vary across deals. Since deal structures are usually created in close coordination with rating agencies, credit enhancement levels reflect agencies'

assessment of risk. [30] find that the level of subordination of the triple-A rated portion of a deal, as well as the probability of overcollateralization and its target level, are larger in whole-loan deals controlling for other determinants of ratings, indicating that rating agencies accounted for the greater moral hazard in those deals as a risk factor. I extend their results to auto loan ABS and to lower-rated tranches, and strengthen them through the use of more sophisticated and precise measures of credit enhancement. Another paper that investigates differences in credit enhancements between whole-loan and originator deals is [69], who however finds no differences in subordination and overcollateralization. The reason for this finding may be that she studies subprime deals, where as discussed above asymmetric information does not seem to play a big role for loan quality. There is one other paper to my knowledge that specifically addresses the question of whether rating agencies account for threats to credit quality due to asymmetric information problems. [82] study commercial MBS, and find that firms whose stock price has recently fallen make worse mortgages, and their securities receive worse ratings. The explanation they propose is that firms in financial trouble are more concerned with short-run profitability than with reputation.

Finally, other papers have studied effects of incentive issues on tranche pricing. [30] focus on the pricing of triple-A rated securities and find, in a parsimonious model, that spreads in low-documentation whole-loan deals are 11 bps larger, while there is no effect in high-doc deals. I find no difference in the pricing of top-rated tranches from whole-auto loan ABS deals. It thus seems that from this perspective prime auto loan ABS resemble high-documentation mortgages, in that investors rely on rating agencies for pricing triple-A tranches, even though loan quality is affected by incentive issues and rating agencies account for this like in low-doc MBS. On the other hand, I do find that investors price incentive issues in lower-rated tranches beyond what is accounted for by ratings. [37] and [38] provide a similar conclusion for a broad sample of securitized debt, showing that tranches from deals where the securitizer services the collateral have lower spreads. Investors acknowledge the reduced moral hazard in this case.

The remainder of this paper is organized as follows. In the next Section I lay out my hypotheses and empirical questions. Section 1.3 introduces my dataset, and Sections 4, 5, and 6 investigate pool losses, tranches ratings, and the pricing of securities in turn. Section 7 concludes.

1.2 Background and hypotheses

1.2.1 Auto loan securitization

In a securitization transaction, a so-called deal, the cashflows from a collection of financial assets, the collateral, are pooled and structured to create securities ("tranches") that are backed by the collateral. In auto loan securitizations, the collateral consists of retail instalment loans secured by new and used cars and light trucks. The company owning the assets, the securitizer,[1] transfers them in a true sale to a special purpose vehicle (SPV) that issues the tranches, and which is bankruptcy-remote from the securitizer. Through this arrangement the loans are removed from the balance sheet of the securitizer, whose creditworthiness is separated from the risks of the securities issued. The tranches are backed solely by the assets of the SPV.

Collections from the collateral are distributed to security holders according to fixed rules specified in deal documents, the deal's so-called structure. The structuring of cashflows is an important aspect of securitization permitted by the SPV construction, and it results in the creation of securities with different payoff and risk characteristics. The dominant structural feature in auto loan ABS is the senior-subordinated

[1] Another common term for the company that arranges a transaction is sponsor.

structure, or "waterfall", by which principal of securities is amortized successively. Tranches are ordered by a seniority ranking, and collateral cashflows are used to pay down their principals one after the other, so that subordinate tranches receive only interest payments until all superordinated ones have been paid off. Collateral losses first accrue to lower-ranked securities, providing a buffer to more senior ones, and reducing their credit risk. An alternative to the pure waterfall is to introduce a pro-rata element into the senior-subordinated structure. While senior tranches that are rated AAA pay off sequentially, subordinated ones receive principal in parallel as long as certain credit protection levels are maintained.

Credit enhancements are all structural features of a deal that are aimed at protecting securities from losses. Creation of subordinated securities that absorb losses as just explained is the most important way this happens in auto loan ABS. Other common forms of credit enhancement are an excess in pool principal over the amount of tranches sold, an excess in pool interest receipts over what is required for tranche interest payments, additional cash that the securitizer deposits with the SPV, and financial guarantees by bond insurers. Credit enhancements allow the creation of different securities from a homogenous pool of car loans, and in particular they permit financing a large part of the pool at triple-A conditions, which is crucial for reducing financing costs.

Securitization in the United States was pioneered by the mortgage guarantors Fannie Mae and Freddie Mac in the 1970s with the issuance of pass-through securities. In 1983, the first collateralized mortgage obligations were issued that allowed the creation of different classes of securities ([4]). Shortly afterwards in 1985, lenders of consumer debt adopted the technique. The markets for securities backed by car loans, as well as for other collateral types such as credit card debt, saw rapid development, and in 1995 annual issuance of auto loan ABS had reached $30 billion dollars. The most important feature of securitization was that it provided a new source of funding for lenders. Securitization allows, to a large extent, the decoupling of the financing costs of loans from the overall creditworthiness of the lending company. This leads, in combination with the structuring of the cashflows, to a reduction in financing costs. In addition, securitization provides the opportunity for lenders to diversify their financing structure, and removing loan pools from the balance sheet can have beneficial effects for capital requirements. Securitization as a form of funding is used by all types of lenders active in auto financing. In many cases, securitizers in auto loan ABS are banks or finance companies that perform the three major functions of value added in auto lending, originating loans which they finance themselvces while retaining servicing rights. In the following, I will refer to transactions by such vertically integrated firms as "originator deals".

Another secured funding option for auto lenders is the market for whole loans, where portfolios are traded with full transfer of ownership. For the most part, loan originators retain servicing rights of the loans they sell, but sales also take place on a servicing-released basis ([64]). The whole-loan market developed later than the auto ABS market, and in the 1990s, when auto loan securitization saw enormous growth, it consisted mostly in small transactions ([72], [1]). In the 2000s, however, the market became more active, and a number of auto lenders, among them the captive arms of the "Big 3" US carmakers, made large transactions. One reason driving this increase were unfavorable unsecured lending conditions faced by firms that made them seek new sources of funding. Another reason to engage in loan sales is the complete capital relief it can provide if the seller does not keep any exposure to the loans ([42]). The growth in whole-loan sales gave rise to another type of auto loan ABS deal, in which investment banks, or investment banking arms of commercial banks, securitize whole loans. This practice had existed in the mortgage realm for a long time. Originators of loans securitized in these deals were often companies that were active directly in securitization markets themselves as well. In the following, I will refer to such deals as "whole-loan deals".

1.2.2 Incentive issues

The focus of this paper is to study differences between originator deals and whole-loan deals regarding informational frictions between originators, securitizers, and investors arising due to asymmetric information in credit risk transfer, and investigate the implications for collateral performance as well as for ratings and tranche pricing. My hypothesis is that moral hazard issues are stronger, and thus collateral quality lower conditional on observable risk characteristics, in deals where an investment bank securitizes car loans from other originators. This is due to two factors. First, originator incentives to transfer high-quality loans differ between securitization deals in which they are the securitizer on the one hand, and whole-loan sales on the other, since in the former they maintain a direct stake in the cashflows from the collateral. Second, in whole-loan securitization deals there is moral hazard on behalf of the securitizing investment bank in addition to the originator.

Originators have superior knowledge about loans they have made, both over investors in tranches when they securitize a pool and over the buyer of a portfolio in a whole-loan sale, despite information transmission to those agents. Investors in tranches receive a deal prospectus in which the loan pool is described, containing pool averages or distributions regarding a number of loan characteristics, as well as summaries of subpools. Pre-sale reports by rating agencies generally contain additional information. Buyers in whole-loan transactions have access to all hard information the originator has recorded about the loans in the receivables files. Nevertheless, investors and buyers remain at an information disadvantage, since the originator possesses relevant private knowledge about the receivables. Originators are directly informed about the lending standards and the screening and verification intensity that were applied in the origination process. They may have gathered so-called soft information that cannot be conveyed to loan buyers, such as about borrowers' future job prospects ([71]). Quantifiable information plays a more important role for car loans than for other types of loans ([55]). There is the possibility of misrepresentation of loan characteristics, possibly in collaboration with borrowers ([8]). Finally, the originator has private information on the process by which the receivables were selected from their overall portfolio of loans. An originator may be able to adversely select contracts to be sold, drawing on the complete performance history of loans they have originated. The upshot of this is that when a pool of loans is either sold or securitized there is a lemons problem, since third parties cannot accurately observe the true quality of the pool. Quality may be impaired both due to low screening efforts as well as due to selection of worse-quality loans. In addition, the fact that the originator is usually also the servicer of the loan pool gives rise to another situation of moral hazard. The servicer of a deal is the agent responsible for loan collections and handling delinquencies, and their quality of operations can affect the performance of loans in a significant way. However, the effort expended by the servicer is not perfectly observable by outsiders, and cannot easily be contracted on. The originator thus has an incentive to reduce costly servicing effort ([31], [48]).

An important difference between originator and whole-loan deals are the incentives for originators arising from differences in the stake they keep in the loans. As explained above, in an auto loan ABS the SPV is bankruptcy-remote, meaning that its assets cannot be part of a bankruptcy of the securitizer, and neither has a securitizer any obligations to the SPV since the transfer of the loan pool is conducted as a true sale. The securitizer does, however, own the residual interest in the SPV. This means that all pool cashflows and other SPV assets not used to service tranche holders' claims or other obligations of the SPV, such as servicing fees, revert to them. And it implies that securitizers holds a direct stake in their deals, or have so-called "skin in the game". Specifically, as owners of the residual interest, they take the first losses. As a consequence, incentives of originators differ between deals in which they are the securitizer and ones where they are not. The moral hazard to omit costly screening and monitoring efforts, as well as to adversely select loans, is weaker when the originator maintains equity in loans as securitizer. This is true in particular since in almost all auto loan ABS all losses are bourne by the residual interest, in which case a marginal reduction in pool cashflows affects the securitizer, and only them. On the other hand, if an originator sells in the whole-loan market, the moral hazard is fully operational, since the loan buyer bears all losses. A loan portfolio sold by an originator in the whole-loan market is thus expected to be of lower credit quality, controlling for observable characteristics, than a securitized pool.

In addition to moral hazard on behalf of the originator, pools in whole-loan deals may also be subject to adverse selection of loans by the investment bank acting as securitizer. In most cases, investment banks securitize only parts of the portfolios of loans that they buy from lenders. The incentive problem is structurally identical to that of originators securitizing, but the scope for adverse selection in this context is smaller, since securitizing investment banks do not have the same level of information about loans as originators do. Nevertheless they maintain an information advantage over investors in tranches. On the other hand, investment banks generally play only a very limited role in servicing, taking formal responsibility as master servicer while contracting with originators or third parties to complete all operational tasks. Moral hazard on behalf of securitizers is thus expected to stem only from adverse selection.

1.2.3 Credit ratings and security pricing

Credit ratings play an important role in bond markets. They are universally observed by market participants, are embedded into financial regulations, and feature in most academic studies on the subject. Credit rating agencies serve an economic function as delegated monitors, reducing informational asymmetries and transactions costs and thus increasing market efficiency ([44], [26]). Ratings are particularly important in the market for securitized debt. More than for corporate bonds, the complexity of structured finance securities and resulting large costs faced by investors to analyze them create a strong role for information production by rating agencies ([26]). Since the inception of the market, most asset-backed securities have been rated, because issuers wanted to attract investors and to make tranches comparable to other types of debt ([26]). Furthermore, ratings have official functions in financial markets, e.g. for calculation of bank risk-weighted assets, or in bylaws restricting investments by pension funds. In summary, ratings are expected to play a big role in agents' decisions, and to affect pricing of securities.

The importance of ratings for securitized debt markets created enormous business opportunities for the rating agencies in the years before the financial crisis, when securitized debt markets grew strongly. However, when mortgage losses rose starting in 2007, ratings performance underwent an unprecedented decline. For certain asset classes, such as subprime RMBS and ABS CDOs, up to half of triple-A rated tranches were downgraded to CC or lower, implying that they defaulted ([2], [61]). Due to these events, rating agencies' role in the developments leading up to the crisis is in retrospect seen critically. They are blamed for insufficiently taking into account risks to collateral quality, in part regarding how incentives led to declines, and ratings are in retrospect widely regarded to have been overly optimistic. The issuer-pays compensation system may also have played a role, since ratings quality can be negatively affected by incentives to issue better ratings in order to attract more business. Rating agencies are chosen and paid by issuers of bonds, giving rise to a conflict of interest ([13]). One specific example of such behavior is so-called rating catering, where an agency adjusts its assessment to that of competitors so as not to lose business ([49]). Consistent with rating agencies reacting to such incentives, [12] provide evidence that an increase in competition in the rating industry led to a decrease in rating quality and to an overall rise in the level of ratings.

In their analysis, rating agencies take into account a large amout of information to assess the risks of a loan pool and of the tranches created. At the core of the process is a loss expectation for the underlying pool. This is formed using information on the past performance of loans by the same originator, as well as other observable characteristics. The most important of these is a pool's seasoning, defined as the weighted average age of loans at the time the deal is issued. Older loans are farther along their expected loss curve, so that seasoning reduces the amount of credit risk in a pool. Other factors are loan terms, credit scores, and geographic distribution. Another part of the assessment are investigations of the agents involved in the transaction, most importantly the originator and servicer, their quality of operation, business situation, and strategy. Furthermore, agencies take into account the macroeconomic environment. From expectations about pool performance, risks of individual tranches are derived using the deal's structure. In practice, rating agencies can be involved early in the issuing process, and de facto act as advisors how to structure the deal. When rating whole-loan securitizations, agencies consider additional factors that arise in these deals ([42]). One is the issue of "cherry picking", which refers to the selection process of collateral by originators and or securitizers from their respective portfolios of loans, and which can lead to the quality being lower than the standard for a particular originator. Another issue of particular importance in whole-loan deals is servicing, since servicer transfers are more frequent in these transactions. In many cases master servicing is taken over by the securitizer, but this generally does not involve collections, which is contracted out to the originator. Furthermore, rating agencies investigate the economic motives behind a whole-loan sale, and whether it is an exit strategy. In summary, there is reason to believe rating agencies understand the additional informational problems arising in whole-loan deals, and I study their effects on ratings empirically.

Securitizers inform investors about the ratings of the securities offered in the deal prospectus. In the academic literature, ratings have been shown to be the dominant factor driving issuance prices of securitized debt tranches (e.g. [35]). Thus, prices will reflect incentive problems at least to that extent that ratings do. However, investors may not entirely rely on ratings for their assessment of security risks, and may judge the importance of informational frictions differently than rating agencies. I test this possibility by investigating whether issuance spreads of tranches differ between whole-loan and originator deals controlling for credit ratings. Furthermore, I study pricing of triple-A rated tranches, whose creation is an important aspect of securitization since it expands the investor base. A top rating of triple-A, the same as the US government, arguably made securities informationally insensitive. Conventional wisdom suggests that investors did not do much diligence for those securities, which is what [2] finds for RMBS. Accordingly, I expect prices of AAA-rated securities not to differ between the two types of deals.

1.3 Data and variables

The basis for my dataset are US auto loan ABS securities listed on the Bloomberg system. In order to identify whole-loan deals, I collect information on originators and securitizers from deal prospectuses and Moody's website, and investigate, using these sources and supported by coverage in the financial press, their affiliations and whether loan sales took place between them. I define a whole-loan securitization as a deal where the collateral was purchased by the securitizer in the whole-loan market, excluding, however, deals where the collateral was sold after the bankruptcy of the lender, or where the securitizer acquired loans in the course of buying another lender. In the latter cases, the channel I aim to capture is not expected to be operative. Of all deals on Bloomberg issued between 1997 and 2007, I identify 16 to be whole-loan deals. In order to achieve as complete coverage of the market as possible, I compare my sample with deals listed on Moody's website. Of the additional deals listed there one is a whole-loan deal, and I add it to my sample. Given that Moody's rated most deals of my Bloomberg sample, including all whole-loan deals, I expect my coverage of the auto loan ABS market to be close to complete. Since all the whole-loans deals I find were issued between 2002 and 2007, I restrict my dataset to that period. In addition, all whole-loan deals are prime auto loan ABS, which are defined by rating agencies as having a cumulative net loss expectation of 3 percent or less on the underlying loan pool. I therefore only include prime deals in my sample, where for classification in this respect I rely on information from Moody's, and in absence of a rating from Moody's on announcements from other agencies or coverage in the media. Prime deals are the largest segment of the auto loan ABS market, accounting for more than half of annual issuance on average during my sample period. Furthermore, I drop synthetic deals and resecuritizations, and three deals for which very little information is available. Finally, two deals are excluded whose cumulative net losses at 8.6 and 11.2 percent form outliers. They were classified by Moody's as prime, but three other deals issued by the same issuer in the same year were classified as near-prime. My final data set consists of 206 deals, of which 17 include whole-loan collateral. Throughout the paper, the key variable is a dummy indicating whole-loan deals, or tranches that belong to one.

Information on the tranches of each deal, their principal balances, coupons, seniority ranking, and issuance dates are obtained from Bloomberg, and from Moody's for the additional whole-loan deal. For each pool, I take as date of loan origination the deal issuance date minus the weighted average age of loans in the pool. The most important performance measure for car loan pools are cumulative net losses, which are defined as the percentage of initial pool principal that is charged off over the lifetime of the loans, net of recoveries. I use data from Barcap Live, supplemented with information from Moody's. My data also includes a number of variables characterizing the loan pools, which is generally available from Bloomberg, but in many cases had to be supplemented with information from deal prospectuses or Moody's. "Seasoning" is defined as the weigthed average age of loans at the time of deal issuance. "Original term" is the weighted average initial maturity of loans in the pool, where I apply a normalization by year of origination in order to account for general trends in the market-wide standard for loan terms. From the raw value I subtract the mean weighted average maturity of prime loan pools originated in the same year. The weighted average coupon of a pool is also normalized to account for systematic changes in interest rates. I subtract the 5-year Constant Maturity Treasury rate at the time of pool origination. The average loan size in a pool is calculated from data provided in pool prospectuses. These often pertain to the actual securitized loan pool, and otherwise to representative statistical data. "Percent used" refers to the fraction of pool principal extended for the purchase of used cars. I use two variables characterizing the geographical distribution of a loan pool. "Top state" is the fraction of pool principal located in the most strongly represented state. The other variable is a dummy ("Small states") indicating that at least two of the three top states of the pool by principal are not among the eight US states that over 10 million residents in 2005. The first variable measures the degree to which a pool is concentrated in a single states, whereas the second one pertains to nationwide diversification. "Prefund" is a dummy variable indicating that SPV assets include a cash deposit that is intended for the additional purchase of loans within a given time frame. Weighted average FICO scores are available only for a limited number of deals, since this information is missing even from many fee-based deal reports by rating agencies. Credit scores have traditionally played a less important role in auto ABS than in other asset classes ([3]). Test including credit scores in this paper mainly serve the purpose of robustness tests.

I further gather information on loan originators and servicers. Deal prospectuses almost always contain data on the historical performance of loans by the same originator, covering the past two to seven fiscal years as well as the most up-to-date information on the current fiscal year. I define the variable "Previous losses" to be the annual net charged-off amount as a fraction of average principal amount outstanding, averaged over the past two full fiscal years. This measure is available for all but two deals in my sample, both of which are whole-loan deals. In one case, the prospectus does not contain historical data since the origination channel had only recently been established, while in the other case no prospectus is available. For robustness, I conduct tests omitting historical losses from the analysis. Next I classify loan originators with respect to the nature of their business, where I distinguish between three types: nationally chartered banking associations or federal savings banks ("banks"), finance companies that are subsidiaries of domestic or foreign carmakers ("captives"), and other non-bank lenders ("finance companies", abbrev. FC). In some cases, the underlying loan pool is made up by loans from multiple originators, which can be up to four firms in one case. For deals where not all originators are of the same type, I use the type responsible for the majority of loans. I also gather information on the credit ratings of originators and deal servicers, where I substitute with parent company ratings if a firm is not rated individually. In cases where multiple agents are involved in servicing, I focus on the master servicer, since my aim mainly is to proxy for servicing stability, and the master servicer is the agent considered relevant in this respect by rating agencies. The data is obtained from Bloomberg for the three major agencies Fitch, Moody's, and Standard & Poor's, and in one case augmented with information directly from Moody's. Of the multiple ratings a company can have from the same agency, I use the categories "Senior Unsecured Debt" for Fitch and Moody's, and "Long-Term Local Issuer Credit" for S&P. In cases where one of these categories is not available, I substitute with other long-term broad rating categories. Originator ratings are recorded at the time of pool origination, while servicer ratings are at deal issuance.

The structuring of cashflows plays an important role for the risk of individual tranches. I collect data on deal structures from prospectuses, supported by reports from Moody's. Credit enhancements are discussed below in Section 1.5.1. If the level of interest rates in a pool is low relative to the obligations of the SPV in terms of tranche coupons and other obligations such as servicing fees, then usually a part of the assets of the SPV are assigned the role of a yield supplement. These funds, which can take the form of cash in a yield supplement account, or the form of additional pool principal (yield supplement overcollateralization, abbrev. YSOC), are intended to make up the difference. The reason for low loan rates are often subvention programs of carmakers, the goal of which is to boost sales by extending cheap credit. I quantify the amount of yield supplement of a deal as the size of the yield supplement as a fraction of the initial pool principal balance. In deals with yield supplement in the form of overcollateralization, an adusted pool balance is generally used for deal calculations, which is defined as the nominal balance of the pool, minus the amount of it assigned as yield supplement overcollateralization. Finally, I define an indicator variable ("Pro rata") that is 1 for deals, or tranches of deals, were subordinated tranches pay back in parallel to senior ones.

On the individual security level, I exclude tranches from my sample that are interest-only bonds, that have an original principal balance of zero, or that pay no interest. I collect information on tranche ratings at issuance from Bloomberg for Fitch, Moody's and Standard & Poor's, which were by far the most important rating agencies in the auto loan ABS market during my sample period. Rating symbols are converted to numerical values using the following conversion, where a unit corresponds to a rating notch: AAA = 15, AA+ = 14,..., BB- = 3.[2] A tranche's issuance rating is then defined as the mean value across ratings it received from the three agencies. A small number of tranches were also rated by DBRS, and I will control for existence of such ratings with a dummy in regressions. I also gather information from Bloomberg on tranches' weighted average lives (WAL), which is the standard measure of maturity for structured finance securities. WAL is defined as the average time until principal repayment, weighted according to the size of each principal payment, while interest payments are disregarded. Since auto loan ABS tranches do not have fixed principal repayment schedules, WAL is in expectation. For subordinated tranches where WAL is not available on Bloomberg, I estimate it in the following way. For reference, I find

[2]Throughout this paper I will use the rating terminology of Fitch and S&P, unless otherwise noted, or the rating is specifically from Moody's.

the next-more senior tranche for which expected WAL is available, and calculate the difference realized ex-post WAL. Then I define the estimated WAL in the way that the difference to the realized WAL is the same as for the reference tranche. Furthermore, for one tranche I estimate WAL by comparing to the previous and following deals by the same issuer, which had identical structural features.

My pricing measure for tranches at issuance is the coupon spread, which is defined as the difference between a tranche's coupon and a Treasury rate matched to the weighted average life of the tranche. For the pricing analysis I restrict myself to tranches that pay a fixed coupon. Daily Constant Maturity Treasury rates from the Board of Governors are available for maturities of 1, 3, and 6 months and 1, 2, 3, 5, and 10 years,[3] where I use rates timed to the last date before a tranche's issuance date when all T rates are available, which is generally at most three days earlier. The rates are interpolated cubically to obtain values for intermediate WALs. I drop spread observations for tranches where the issunce price deviates from par by more than 1 percent, which exclude 3 tranches. However, for 71 securities no price is available.

1.4 Moral hazard and loan pool performance

The first empirical question I investigate is whether auto loan pools of whole-loan deals perform worse due to the greater moral hazard on behalf of originators and securitizers. My strategy is to regress cumulative net losses on the whole-loan dummy, while controlling for all attributes of a pool that are correlated with its likelihood of being securitized in a whole-loan deal, and that at the same time inform about the quality of the pool. In other words, I rely on the conditional independence assumption (CIA) that whether a loan pool is part of a whole-loan or an originator deal is

[3] Since the 1-month rate is not available before 7/31/01, I use the Effective Federal Funds Rate instead before that date.

unrelated to its potential loss outcomes in both cases, conditional on control variables included in the regression. If this holds, the "treatment" of being a whole-loan pool is as good as randomly assigned, and the estimated coefficients have a causal interpretation regarding its effect on loan quality. I argue that the CIA is justified, since the control variables I use exhaustively inform about the quality of loans, so that there are no missing factors that can explain the connection between pool performance and whole-loan deals that I find. My covariates include a number of aggregate pool characteristics that are related to the quality of the loans, and by themselves have much explanatory power. It would be possible, however, that other loan attributes for which I do not control, such as loan-to-value ratios, payment-to-income ratios, or the distribution across vehicle types, introduce a selection bias into my analysis. In order to avoid this, I include two variables that comprehensively reflect an originator's loan quality, and thus can account for any relevant omitted factor. One is the recent loss experience of loans from the same originator, and the other is the originator's credit rating.

A possible problem with using originators' historical losses as control variable is that they may themselves be influenced by incentive issues associated with loan sales. However, any such effect is likely to be small, since sold loans generally only account for small fractions of lenders' portfolios. Furthermore, if the whole-loan dummy is correlated with having sold loans previously, as seems reasonable, the resulting bias lowers my estimates, thus only making them more conservative.

An originator's credit rating reflects the quality of loans they originate, since as part of their assets they affect the overall riskiness of the firm. The rating can also inform about a lender's quality of operations and financial situation, both of which can have an impact on loan quality. In addition, originator rating is an important control variable since there are reasons beyond loan quality why it may be related to the likelihood of selling loans in the whole-loan market versus securitizing or keeping them. One is that lower-rated lenders are more likely to be small and have fewer capacities to engage in investment banking activities like securitization. Second, because of their worse ratings, they are less likely to encounter good conditions in the primary ABS market, since the rating affects their reputation as servicer and securitizer ([37]). As a consequence, originator rating is an important control variable since it is related to both the "treatment" and the outcome.

Table 1.1 presents descriptive statistics at the deal level. Cumulative net losses are larger on average for pools of whole-loan deals, by 0.36 percentage points, even though this difference is not statstically significant. In line with this, whole-loan pools appear to be more risky ex-ante with respect to a number of other characteristics. They have greater historical losses, by 0.37 percentage points, higher coupons, longer loan terms, and smaller loan amounts. Originators of whole-loan pools also have lower credit ratings, but some originator-securitizers are not rated at all. Furthermore, whole-loan pools are more likely to be concentrated in one state, and slightly more likely to not be nationally diversified. Other characteristics, however, make whole-loan pools look less risky. They have more seasoning, by over 6 months, which makes intuitive sense since there are so-called "lock-out" provision preventing the buyer to resell whole loans for a certain period ([42]), or it may take a securitizer time to arrange a deal after they bought loans. FICO scores are also higher in whole-loan pools. Finally, of the three originator types bank collateral is most likely to end up in whole-loan deals, and there is only one deal with collateral from finance companies.

Table 1.2 shows results from regressions of cumulative losses on the whole-loan dummy and control variables. In order to account for time-varying external factors affecting all pools, I include issuance-year fixed effects. In the first specification, I include the main pool risk characteristics seasoning, original term, WAC, percent used, and average loan size, as well as the amount of yield supplement and a dummy for loans originated by captive finance companies. A greater yield supplement amount indicates a larger share of incentive loans, whose quality is expected to be lower conditional on other attributes. Similarly, loan pools originated by captives may be of lower quality, since they have an incentive to be lenient in their credit decisions to boost car sales. I only control for collateral by finance companies in robustness tests later, since in the prime market they compete for the same customers as banks and captives. Controlling for these factors, I find that loan pools in whole-loan transactions have 0.64 percentage points higher losses than those in originator deals. A similar result is obtained when including the FICO scores of loan pools, which, however, reduces my sample significantly. I exclude percent used and average loan size in specifications with FICO, since coefficients of these variables change strongly and switch signs from their values in specification 1. I attribute these effects to overfitting, since FICO is only available for a subsample. I then add previous losses and originator rating to the regression (Specification 3). The coefficient of the whole-loan dummy, even though smaller at 0.36 percentage points, is statistically significant at the 5-percent level. Greater moral hazard along the securitization chain of whole-loan deals thus leads to lower loan quality in these deals, and the effect is economically meaningful. It equals a fourth of overall mean losses on prime pools during my sample period, and a third of their standard deviation. I also test versions of the model without historical losses, and with FICO scores. The absence of previous losses, even though they are not statistically significant in equation 3, increases the effect of the whole-loan dummy and its significance, and this is not driven by the two whole-loan deals without information on previous losses. In equation 5 that includes FICO scores, the size of the estimate of interest from equation 3 is confirmed, even though the statistical significance is lost.

I conduct a number of robustness checks. In column 6 I add a dummy variable for deals whose loans were originated by independent finance companies, to account for systematic differences in loan quality not accounted for by my other covariates. If such differences are present, I need to control for FC, since finance company collateral is also less likely to be in whole-loan deals. However, my estimates are unchanged when controlling for finance company collateral, and the coefficient on FC is small and insignificant. In column 7 I allow for the possibility that originator ratings have a different meaning across originator types. Bank are more strongly supervised and regulated, and captive finance companies always have a carmaker parent associated with them. I find that in this specification my finding for the whole-loan dummy is even stronger. Ratings of captives are found to be more closely related to pool quality than those of banks, while they do not matter for finance companies (many of which are unrated). In columns 8 ot 10 I add controls regarding the existence of a pre-funding account and the geographic distribution of loans. All these factors possibly affect pool quality and may be correlated with the whole-loan dummy. Prefunding introduces the risk that subsequently added loan are not of the same quality. My previous result is confirmed in these specifications. In the last column I exclude deals where the originator was not involved in servicing the loans, but instead all functions were assumed by the securitizer or a specilialized third-party servicer. Such deals are always whole-loan deals, but the servicer incentives resemble those of originator deals. If the servicer is affiliated with the securitizer, then the moral hazard should be mitigated in this respect. Correspondingly, I find the effect of the whole-loan dummy to be somewhat larger in this case.

My results are underlined by the fact that all of the main control variables are found to be meaningful determinants of losses, or at least have the expected coefficient signs. Higher coupons, longer maturities, and less seasoning are associated with lower loan quality, as are captives as originators, and more yield supplement. Greater historical losses indicated lower loan quality, although the coefficient is not significant. The coefficient of percent used is positive, and the one on loan size is negative. Originator ratings are strongly related to the quality of loan pools. A rating improvement by one notch is associated with cumulative losses that are about 0.07 percentage points greater, and the fixed effect for unrated originators corresponds to a rating of between AA- and AA. The fact that the control variables matter for the dependent variable is also reflected in high adjusted R-squared values. In summary, the results provide strong evidence overall for the role of greater moral hazard in whole-loan deals for pool quality.

1.5 Do rating agencies take incentive issues into account?

I now turn to the question of whether credit rating agencies are able to recognize the greater moral hazard associated with whole-loan deals when making their assessments. The credit risk of a tranche is mainly a function of two factors: the quality of the underlying loan pool, and the amount of credit protection provided by the structure of the deal. If pools' loss expectations that agencies base their ratings on account for the lower quality in whole-loan deals, then ratings of those tranches should be worse, conditional on credit enhancements and observable pool characteristcs. In order to test this hypothesis, I employ two empirical approaches. The first one are linear regressions of numerical rating values, where I exclude tranches rated triple-A. The second approach are ordered logit regressions of letter rating classes. In both cases, I use a dummy variable to identify the difference between tranches of whole-loan and originator deals due to adverse incentives.

1.5.1 Credit enhancement

In order to investigate the effect of moral hazard in whole-loan deals on rating outcomes, it is necessary to control for credit enhancements as key determinants of credit risk. I analyze deal structures to obtain measures of protection for each tranche. Conceptually, one can distinguish between hard credit enhancements, which are available with certainty in a fixed amount, and soft credit enhancements, whose magnitude is unknown ex-ante ([29]). In auto loan ABS, hard credit enhancement can take a number of different forms. Subordination refers to outstanding principal of tranches with a lower seniority ranking that provides a loss buffer for more senior ones. Overcollateralization is pool balance in excess of the total amount of tranche principal outstanding, which in the same way acts as a loss buffer for all tranches. A reserve account contains funds owned by the SPV that are available for payments to tranche holders in the case of pool losses. Finally, a few deals are protected by cash available through a liquidity note. Due to their similar nature, I will treat the latter as reserve account balances in the following. The level of hard credit enhancement of an individual tranche is expressed in terms of the fraction of outstanding pool principal that can default before the tranche suffers a loss. At the time a deal is issued, it is thus equal to the sum of the tranche's subordination, the deal's overcollateralization, and the reserve account balance, divided by the pool size (or, in the case a deal contains a yield supplement, the adjusted pool size, see Section 1.3). I call this variable "hard c/e".

Soft credit enhancement in auto loan ABS is usually provided in the form of excess spread. This is defined as interest receipts from the underlying loan pool in excess of the level required to pay interest on the tranches and service other obligations of the SPV such as servicing fees, and is uncertain since it relies on loan payments.

Excess spread that is available in a given period can be used for amortization of tranche principal or deposited in the reserve account for later use. In both cases it increases the level of hard credit enhancement available, either through a larger reserve account or through more overcollateralization. However, excess spread can also be immediately released to the securitizer. The extent to which expected excess spread is made available to support tranches is fixed in deal documents. Such provisions take the form of target amounts for reserve accounts, overcollateralization, or the sum of both, which exceed initial levels and are expected to be reached by the use of excess spread. These targets are generally met, so that their levels matter more than the amount of excess spread that in principle could be available in a deal, since additional pool collections are released to the securitizer. Each deal has at most one target, and they are formulated either as a percentage of the initial pool size, or as a percentage of the current pool size outstanding. For the quantification of the amount of credit protection provided by excess spread in a deal, I distinguish between these two cases. If the target is formulated as percentage of initial balance, it is directly comparable to the initial level of the respective credit enhancement device. In this case, I use the target instead of the initial value in the above calculations of hard credit enhancement to obtain the variable "hard c/e (target)". If the target is formulated as percentage of outstanding balance, I define the variable "excess spread" to be the difference in percentage points to the initial level. Even though in this calculation I am comparing fractions of different amounts, it is a useful means to compare excess spread across deals.

The deals in my sample can be divided into two groups regarding their structures. In deals of one group, tranches pay off principal strictly successively in a pure waterfall. In the other group, only triple-A rated tranches follow a waterfall, while subordinated tranches receive principal in parallel to senior ones. The guiding principle in this pro-rata structure is that subordinated tranches initially provide credit protection to more senior ones, but once other forms of credit enhancement (over-collateralization or reserve account) have been built up using excess spread, those tranches are no longer needed as buffers. Parallel distributions generally only start after some time, and are conditional on achieved levels of the other enhancements. Furthermore, most such deals contain so-called triggers that can lead to a conversion of the structure to a pure waterfall. Triggers are defined in terms of the performance of the underlying pool over certain timespans during the deal's lifetime. This arrangement makes it unlikely that tranche escape losses they would otherwise suffer by being paid off early, and being a concurrent-pay tranche should thus not reduce credit risk. I control for tranches from pro-rata deals with a dummy.

1.5.2 Linear regressions of numerical rating values

The large majority of auto loan ABS tranches carries a top rating of triple-A. In order to avoid issues of truncation, I exclude these securities from the linear regressions. The identification strategy for the effect of being a tranche of a whole-loan deal on ratings is to account for other potential drivers of credit ratings in the regressions. The main factors I need to control for are the loan quality of the pool, and the credit protection of a tranche. In order to proxy for the former, I use the variables that were included in regressions of pool losses above in Section 1.4. Credit enhancements are mainly captured by the variables hard c/e (target) and excess spread introduced in the previous section, but I also consider two other variables related to deal structure for robustness. One is the pro-rata deal dummy defined above, since there may be tranche risks associated with this structure. The other is a tranche's weighted average life divided by the weighted average maturity of pool loans at the time of deal issuance. This relative measure of WAL may provide additional information about the credit enhancement, since the later a tranche is expected to pay back, the less likely it is to benefit from protection provided through losses accruing to other tranches first.

There is a number of additional factors that rating agencies take into account when issuing ratings. One is the stability and quality of operations of the deal's servicer, which I proxy for with its credit rating. The macroeconomic environment also matters for agencies' loss expectations ([64]), despite their general intention of rating "through-the-cycle". This may be due to the shorter life span of auto loan ABS tranches than many other bond classes. I include the unemployment rate and the level of the Used Vehicle Value Index published by Manheim Inc., both measured at the time of deal issuance.

Table 1.3 documents characteristics of tranches rated below triple-A. Ratings of whole-loan tranches are on average lower than for originator deals, by more than one rating notch, and this does not correspond to lower levels of credit protection. Both measures of hard credit enhancement are on average about equal across deal types, and excess spread is in fact larger in whole-loan deals. This makes sense, since losses on whole-loan pools are also larger on average. A marked difference is observed between the deal types regarding tranches' relative weighted average lives, which are significantly shorter in whole-loan deals. This is a consequence of the fact that most whole-loan deals have pro-rata structures, in which subordinate tranches pay back more quickly. Yet also when considering only pro-rata deals, relative WALs of whole-loan tranches are lower. This can be a consequence of more "aggressive" deal structures, where subordinate tranches are paid back as quickly as possible to save interest payments ([32]).

Table 1.4 shows results from linear rating regressions. As a preliminary specification I only control for historical losses as key measure of pool quality, and the most important structural variables (hard c/e (target) and excess spread), as well as year-of-issuance fixed effects. I find a highly significant negative effect of the whole-loan dummy. The estimate implies that, for identical credit protection and observable pool characteristics, ratings in whole-loan deals are more than one rating notch lower than in originator deals. This result is strengthened in equation 2, where I include the main variables relevant for pool quality from loss regressions as well as the unemployment rate, and in an unreported specification which additionally allows for different slopes of originator rating across originator types. In equation 4, I test a model without historical losses, which allows inclusion of two additional whole-loan tranches. In this specification the effect of the whole-loan dummy is markedly larger, which is likely due to an omitted-variable bias, since rating agencies' approach is actuarial, so that historical losses play an important role.

I conduct a number of other robustness tests. Servicer rating is highly correlated with originator rating, since in many cases they are identical, so that in order to control for the effect of the servicer, I need to exclude originator rating. Equation 5 shows that the coefficient on servicer rating is much smaller and less significant, while in this specification the whole-loan effect is larger. In specification 6, I include a dummy for collateral originated by finance companies, and again find a significantly negative whole-loan effect of one notch, while ratings on tranches backed by FC collateral are estimated to be about 2.5 notches better. Given that there was no indication in loss regressions that colleral by finance companies was better, this finding is surprising, and I consider it an artifact produced by the fact that FC deals are less likely to have multiple subordinated tranches. Unconditionally, average ratings on subordinate FC tranches are more than one notch better than on other collateral types. Furthermore, I test robustness to the inclusion of the used vehicle price index, the "small states" dummy for not nationally diversified pools, and the dummy for deals with a prefunding account, respectively. The whole-loan dummy's size and significance remain unchanged in all cases, while the coefficients on the additional controls are insignificant or of opposite sign than expected. If deals where the originator was not involved in servicing are excluded from the regression, the effect of whole-loan tranches is somewhat smaller, at -.1.11. Lastly, I include the pro-rata dummy and the relative WAL as additional structural controls. Subordinate tranches that pay off in parallel to senior ones are found to have lower ratings. A possible explanation is that rating agencies are more cautious since credit protection in this structure often relies more heavily on excess spread than on hard credit enhancements. The estimate on the whole-loan dummy in this case is -1.18.

In summary, I find strong evidence that rating agencies assign lower ratings to tranches from whole-loan deals, conditional on all other drivers of ratings, and the effect is sizeable at at least one rating notch. I interpret this as evidence that agencies took into account incentive issues along the securitization chain when rating auto loan securitizations.

1.5.3 Ordered logit regressions of rating classes

An alternative approach for modeling ratings determination is using ordered logit regression. This setup has the advantage over linear regression of numerical rating values that it does not make the implicit assumption that distances between rating categories are equal. I take advantage of the grouping of ratings into letter grades for forming categories of the dependent variable. While in this approach I lose notch-level information on the position of a tranche within a rating grade, it leaves me with at least 14 observations in each category. A benefit of the logit over linear regressions is also that it provides a more natural setting to include triple-A rated securities. My rating categories are thus BB, BBB, A, AA, and AAA, where the last group contains only the most junior triple-A rated tranche of each deal.

Table 1.5 presents results from ordered logit regressions. They confirm the previous finding that tranches from whole-loan deals are rated worse, conditional on other determinants of ratings. In a parsimonious baseline specification that only includes historical originator loss data and credit enhancements, I find an odds ratio of 0.31, which is statistically different from 1 at the 5-percent level. This estimate implies that, for any given rating category k, and conditional all other covariates, the odds of being in category k or higher (as opposed to being in category $k-1$ or lower) are 3.23 ($= 1/0.31$) times larger for tranches from originator deals than for tranches from whole-loan deals. In other words, tranches from whole-loan deals receive lower ratings. This result is confirmed in a number of specifications including additional collateral characteristics, deal structure variables, and the unemployment rate (columns 2 to 4). Even though odds ratios are not significant in all cases, their magnitude is generally similar, varying between 0.34 and 0.38. Table 1.6 contains marginal effects for all covariates for specification 3 from Table 1.5, except for a few dummy variables. The results show that the whole-loan dummy, as well as a number of other variables, significantly affect the estimated likelihood of a rating falling into a given category. Finally, I run an ordered logit regression only including tranches rated below triple-A (Table 1.5, column 5). The result, again, shows that ratings of whole-loan tranches are significantly lower, conditional on other determinants of ratings.

Ordered logit regressions also produce estimates of the probabilities of being in each rating category, conditional on being a tranche from a whole-loan or an originator deal, where the numbers are obtained as averages of probabilities across all observations. For each equation, I report differences in estimated probabilities between the two deal types for each outcome category. For the baseline specification in column 1, the probability of being rated BB, BBB, or A is 3.3, 5.4, and 2.3 percentage points higher for whole-loan tranches, while originator deal tranches are 11 percentage points more likely to be rated AAA.

1.6 Security pricing

Finally, I investigate whether issuance spreads differ between securities from whole-loan and originator deals, controlling for other pricing factors. Given that, as shown above, ratings are affected by differences in incentive issues, I cannot identify the effect of a tranche being part of a whole-loan deal on its pricing in the presence of ratings. But neither can ratings be excluded from spread regressions due to their paramount importance for pricing. My aim is thus to study whether whole-loan tranches are priced differently *holding credit ratings fixed*, and therefore ignoring differences in pricing arising due to differences in ratings between the two types of securities. The analysis is conducted separately for tranches that carry a top rating of triple-A and for lower-rated ones, since the market for structured finance securities is often viewed to be segmented in this way into information-sensitive and -insensitive securities ([61], [50]). In both cases, I study determinants of prices in linear regressions, where again the variable of interest is the whole-loan dummy.

1.6.1 Issuance spreads of subordinated tranches

I begin with regressions of credit spreads of subordinated tranches, in which I control for credit ratings with dummy variables for each letter rating grade. This approach allows non-linear effects on pricing along the rating scale, and is common in the literature. Table 1.7 shows results, where all specifications include year-of-issuance fixed effects. Controlling only for ratings, I find that spreads on tranches of whole-loan deals are significantly larger than on ones from originator deals, by 33 basis points. This finding is robust to the inclusion of the variables I used in the ratings regression above in column 2 of Table 1.4, that is credit enhancements, pool characteristics, and the unemployment rate (ureported results). None of the latter variables show up significant in this regression, indicating that their effect on pricing is captured well by ratings.

I then add variables accounting for other pricing factors. The slope of the yield curve and a corporate bond spread index[4] are timed to the issuance date of securities, so that they capture current market conditions. I include originator type dummies to allow for the possibility that the market is segmented in this way. Since there are no spread observations for subordinate tranches from the one whole-loan deal with finance company collateral, when including the FC dummy the only function of FC observations is to increase power. As a robustness test, I later drop these observations. I include two measures of tranches' liqudity. One is deal size, which is defined as the logarithm of the (adjusted) principal amount of the underlying loan pool, including prefunding amounts, at the time of deal issuance. The other variable proxies for the market's familiarity with a deal. It is based on a deal's ticker, which is a symbol specific to deal from a securitizer. Deals with the same ticker are generally very similar with respect to deal structures and the agents involved, and I define "new deal" to be equal to 1 if a deal is the first with its ticker. For tickers of whole-loan securitizers, sometimes agents involved in deals change, and I classify a deal as new if it represents a major innovation regarding originators within its ticker. Finally, I control for tranches from pro-rata deals, which are expected to pay off in parallel to

[4]The slope of the yield curve is defined as the difference between Constant Maturity Treasury rates for 5 years and 3 months. The corporate bond spread index is defined as the difference between Moody's Seasoned Baa Corporate Bond Yield and the 10-year Treasury rate.

senior ones. These tranches face so-called "extension risk", referring to the possibility that the deal structure converts to sequential pay if loss triggers are met, which would increase their weighted average lives decidedly. Extension-risk is not a credit issue, so that it is not accounted for in ratings ([32]). Column 2 of Table 1.7 shows results including all of these variables. Again, the effect of the whole-loan dummy is positive and significant, implying that tranches from those deal have spreads that are 29 basis point higher, all else equal. All control variables have the expected sign, and in particular the bond spread is an important driver of spreads. Spreads also vary between originator types. The results are confirmed in regressions without tranches from FC deals (column 3).

I conduct further robustness checks. Column 4 includes a larger number of rating dummies, which are constructed so that in each class are at least 11 observations. The effect of the whole-loan dummy is smaller in this case, but nevertheless significant at the 5-percent level. In specification 5, I add tranches' weighted average life to the regression, to allow for the possibility that the term structure of issuance spreads is not flat. Somewhat surprisingly, I find a significantly negative coefficient implying that spreads fall by 14 bps per year of WAL. One possible explanation for this is that it is due to spreads being lower when risk-free rates are high, which is a stylized fact for corporate bonds ([25]). It is also possible that pro-rata tranches are priced against longer-dated risk-free rates than their WAL due to extension risk. In order to allow for these possibilities, I include the WAL-matched risk-free reference rate for each tranche (column 6), or the reference rate only for pro-rata tranches. In both cases the effect of the whole-loan dummy stays significant. In column 8, I control with a dummy for deals with collateral from multiple originators, which is generally viewed to reduce risk since the pool is more diversified ([9]). Consistent with this narrative I find a negative coefficient, and the effect of the whole-loan dummy is larger in this case. Finally, I run regressions without tranches rated BB (columns 9 and 10). In a parsimonious specification I find the effect of the whole-loan dummy to be 18 basis points and significant. The size of the coefficient is robust to the inclusion of other pricing factors.

1.6.2 AAA-rated tranches

Lastly, I turn to the spread investigation for top-rated tranches, where unless otherwise specified I only include the tranche with the lowest seniority ranking among the triple-A rated tranches of each deal. The results in Table 1.8 show that the whole-loan dummy is not significant in any specification. I test a model with only issuance-year fixed effects, one with the covariates from rating regressions (column 2 of Table 1.4), and alternatively without tranches from deals with finance company collateral. I add the weighted average life, and I extent the sample to all top-rated tranches. I then test a version with the pricing factors used in spread regressions of subordinate tranches (column 2 of Table 1.7), which I also extent to all tranches. In specification 8, I include both groups of covariates. Finally, I test the specification in which [30] find that, for low-documentation Alt-A MBS deals, triple-A rated tranches differ regarding pricing between whole-loan and originator deals, but I find no effect. Investor thus price all triple-A rated tranches the same.

1.7 Conclusion

In this paper I study US auto loan ABS and investigate whether deals in which an investment bank securitizes loans acquired in whole-loan sales differ from ones where a lender securitizes collateral they have originated. In whole-loan deals, moral hazard issues arising from asymmetric information between agents involved in the transaction are stronger. I find that, controlling for observable risk characteristics, loan pool losses are larger when an investment bank securitizes whole loans, showing misaligned incentives along the securitization chain are reflected in pool quality. Rating agencies, which are blamed to have insufficiently accounted for risks in structured finance before the financial crisis, are able recognize the incentive problems, and adjust their assessments accordingly. This supports the view that ratings were of good quality in auto loan ABS. Finally, investors demand a risk premium on lower-rated tranches from whole-loan deals to compensate for moral hazard beyond what is accounted for in ratings, but this is not the case for top-rated securities. In the latter case, investors either relied on ratings for their decisions, or they agreed with rating agencies in their risk assessment.

Table 1.1: Deal characteristics. The table shows attributes for the prime auto loan ABS deals in my sample. In Panel A, I show number of observations, number of observations for whole-loan deals, variable mean and standard deviation across all observations, variable means for whole-loan and originator deals separately, the difference between the two types of deals, and the p-value of a test of mean equality between the two groups. In Panel B, I report for indicator variables the total number of observations, the number of positive observations across all deal, and the number of positive observations separately for whole-loan and originator deals. For the variable originator rating (zero), missing values are substituted by zero.

Panel A. Continuous variables.

	Num obs (all deals)	Num obs (wh-loan deals)	Mean (all deals)	Std dev (all deals)	Mean (wh-loan deals)	Mean (orig deals)	Mean difference (wh-loan - orig)	p-value
CNL	206	17	1.35	1.03	1.68	1.32	.36	.166
WA Coupon (%)	206	17	2.12	1.74	2.4	2.09	.31	.485
WA Original term (months)	206	17	60.5	4.42	63.41	60.24	3.17	.004
Seasoning (months)	206	17	6.88	3.89	12.24	6.4	5.83	0
Percent used	206	17	30.15	25.27	31.35	30.04	1.31	.838
Average loan size (1000$)	206	17	17.48	2.69	16.29	17.59	-1.3	.056
YSOC (bps)	206	17	25.25	29.76	18.43	25.87	-7.43	.325
Previous losses (%)	204	15	.76	.43	1.1	.74	.37	.001
Originator rating	177	17	22	3.41	21.32	22.07	-.74	.394
Originator rating (zero)	206	17	22	3.41	21.32	22.07	-.74	.394
Top state (%)	206	17	18.49	9.21	24.14	17.98	6.16	.008
WA FICO	90	7	721.22	20.21	734	720.14	13.86	.081

Panel B. Dummy variables.

	Num obs (all deals)	Num positive (all deals)	Num positive (wh-loan deals)	Num positive (orig deals)
Bank	206	53	11	42
Captive	206	114	5	109
FC	206	39	1	38
Small states	206	25	3	22
Prefund	206	18	1	17
Pro-rata structure	206	102	15	87
Multiple originators	206	11	9	2
Originator not servicer	206	3	3	0
New deal	206	19	11	8

Table 1.2: Regressions of pool cumulative net losses. The table shows deal level regressions of prime auto loan ABS issued between 2002 and 2007. The dependent variable are final cumulative net losses of the underlying loan pool. Standard errors are clustered at the ticker level, and allow for within-ticker heteroskedasticity. Standard errors are in parantheses, and *, **, and *** denote statistical significance at the levels of 10, 5 and 1 percent, resp.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Whole-loan deal	0.64***	0.88***	0.36**	0.47***	0.34	0.36**	0.40***	0.36**	0.41**	0.36**	0.38**
	(0.095)	(0.24)	(0.15)	(0.11)	(0.38)	(0.15)	(0.13)	(0.15)	(0.16)	(0.15)	(0.14)
Captive	0.52***	0.60	0.36**	0.41***	0.15	0.38***	1.36	0.36**	0.48***	0.36**	0.36**
	(0.17)	(0.38)	(0.13)	(0.13)	(0.59)	(0.14)	(1.17)	(0.14)	(0.16)	(0.16)	(0.13)
Original term	0.11***	0.099**	0.098***	0.10***	0.081	0.099***	0.098***	0.098***	0.10***	0.098***	0.098***
	(0.012)	(0.041)	(0.014)	(0.012)	(0.055)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)
Coupon	0.36***	0.42***	0.32***	0.37***	0.36***	0.32***	0.32***	0.32***	0.32***	0.32***	0.32***
	(0.057)	(0.093)	(0.061)	(0.049)	(0.11)	(0.062)	(0.062)	(0.063)	(0.062)	(0.061)	(0.061)
Seasoning	-0.088***	-0.069***	-0.081***	-0.085***	-0.060***	-0.080***	-0.080***	-0.081***	-0.086***	-0.081***	-0.080***
	(0.011)	(0.011)	(0.013)	(0.011)	(0.016)	(0.014)	(0.015)	(0.013)	(0.015)	(0.014)	(0.013)
Percent used	0.074		0.12	0.013		0.098	0.13	0.12	0.28	0.12	0.11
	(0.27)		(0.23)	(0.26)		(0.24)	(0.24)	(0.24)	(0.22)	(0.25)	(0.23)
Average loan size	-35.8		-27.2	-29.7		-27.0	-25.9	-27.3	-27.8	-27.2	-27.1
	(24.1)		(24.1)	(22.8)		(24.4)	(24.7)	(24.4)	(22.5)	(24.1)	(24.2)
YSOC	16.7***	13.0*	8.45**	10.5***	3.71	8.57**	7.88**	8.41**	9.03**	8.44**	8.43**
	(2.56)	(6.32)	(3.63)	(2.76)	(5.25)	(3.59)	(3.73)	(3.77)	(3.61)	(3.59)	(3.65)
FICO score		-1.55**			-1.80**						
		(0.61)			(0.67)						
Previous losses			0.24		0.18	0.25	0.26	0.24	0.20	0.24	0.24
			(0.15)		(0.34)	(0.16)	(0.16)	(0.15)	(0.15)	(0.15)	(0.15)
No originator rating			-1.89***	-1.98***	-2.52*	-1.85***	-1.02	-1.89***	-1.97***	-1.90***	-1.91***
			(0.56)	(0.63)	(1.42)	(0.62)	(1.12)	(0.56)	(0.56)	(0.56)	(0.57)
Originator rating			-0.074***	-0.077***	-0.090	-0.070**	-0.040	-0.074***	-0.073***	-0.074***	-0.074***
			(0.022)	(0.024)	(0.056)	(0.026)	(0.045)	(0.021)	(0.022)	(0.022)	(0.022)
FC						0.087					
						(0.15)					
Originator rating × Cap							-0.039				
							(0.047)				
Originator rating × FC							0.012				
							(0.014)				
Top state								-0.00047			
								(0.0034)			
Small states									0.26*		
									(0.15)		
Prefund										-0.0022	
										(0.22)	
Constant	0.86	11.4**	2.46***	2.66***	15.5***	2.34***	1.54	2.47***	2.37***	2.47***	2.47***
	(0.54)	(4.61)	(0.65)	(0.71)	(4.80)	(0.78)	(1.27)	(0.68)	(0.64)	(0.78)	(0.65)
Issuance year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	206	90	204	206	88	204	204	204	204	204	202
Adj. R^2	0.72	0.78	0.74	0.74	0.78	0.74	0.74	0.74	0.74	0.74	0.74
Num whole-loan deals	17	7	15	17	5	15	15	15	15	15	13

Table 1.3: Tranche characteristics. The table shows attributes for the tranches included in the regressions of final pool losses. In Panel A, I show number of observations across all deals, number of observations for whole-loan deals, variable mean and standard deviation across all observations, variable means for whole-loan and originator deals separately, the mean difference between the two types of deals, and the p-value of a test of mean equality between the two groups. Rating are converted to numerical values according to AAA = 15, AA+ = 14,..., BB- = 3. WAL is a tranche's weighted average life. Relative WAL is defined as a tranche's WAL divided by the weighted average remaining maturity of loans in the pool at issuance.

Variable	Num obs (all deals)	Num obs (wh-loan deals)	Mean (all deals)	Std dev (all deals)	Mean (wh-loan deals)	Mean (orig deals)	Mean difference	p-value
Rating	247	45	8.6	2.4	7.66	8.81	-1.15	.003
Hard c/e (target)	247	45	2.04	2.53	1.99	2.06	-.07	.873
Hard c/e	247	45	2.02	2.53	1.92	2.04	-.12	.772
Excess spread	247	45	1.65	1.19	2.16	1.54	.63	.001
WAL (years)	245	43	3.06	1.04	1.89	3.31	-1.42	0
Relative WAL	245	43	5.7	1.92	3.8	6.11	-2.31	0
Only for tranches from pro-rata deals:								
WAL (years)	103	39	2.01	.48	1.71	2.2	-.48	0
Relative WAL	103	39	3.72	.74	3.3	3.98	-.68	0

Table 1.4: Linear rating regressions of tranches rated below triple-A. The table shows regressions of tranches from prime auto loan ABS deals issued between 2002 and 2007. The dependent variable are tranches' issuance ratings, where numerical rating values are obtained from rating symbols through the conversion AAA = 15, AA+ = 14,..., BB- = 3. Standard errors are clustered at the deal level, and allow for within-deal heteroskedasticity. Standard errors are in parantheses, and *, **, and *** denote statistical significance at the levels of 10, 5 and 1 percent, resp.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Whole-loan tranche	-1.03***	-1.31***	-1.92***	-1.55***	-1.00**	-1.46***	-1.28***	-1.32***	-1.18***
	(0.28)	(0.38)	(0.38)	(0.35)	(0.39)	(0.39)	(0.39)	(0.38)	(0.40)
Hard c/e (target)	77.0***	91.4***	87.7***	89.2***	91.9***	92.4***	91.6***	92.6***	94.5***
	(5.91)	(5.92)	(5.25)	(6.12)	(5.54)	(5.99)	(5.90)	(5.84)	(6.14)
Excess spread	0.43***	0.70***	0.61***	0.73***	0.50***	0.72***	0.70***	0.65***	0.75***
	(0.16)	(0.17)	(0.16)	(0.17)	(0.17)	(0.18)	(0.18)	(0.17)	(0.19)
Previous losses	-2.29***	-1.65***		-1.54***	-1.26***	-1.61***	-1.68***	-1.57***	-1.71***
	(0.34)	(0.41)		(0.43)	(0.41)	(0.41)	(0.43)	(0.40)	(0.42)
Coupon		0.18	-0.059	0.17	0.17	0.16	0.19	0.24	0.22
		(0.16)	(0.14)	(0.15)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)
Original term		-0.25***	-0.30***	-0.26***	-0.22***	-0.25***	-0.25***	-0.25***	-0.28***
		(0.044)	(0.042)	(0.043)	(0.048)	(0.042)	(0.043)	(0.042)	(0.049)
Seasoning		0.21***	0.27***	0.21***	0.21***	0.21***	0.21***	0.24***	0.21***
		(0.039)	(0.035)	(0.040)	(0.038)	(0.040)	(0.038)	(0.041)	(0.042)
Percent used		0.0016	0.0072	0.0015	-0.0048	0.0016	0.0024	0.0028	-0.0026
		(0.0098)	(0.0090)	(0.0098)	(0.0091)	(0.0095)	(0.0094)	(0.0098)	(0.010)
Average loan size		416.8***	502.5***	434.6***	401.4***	418.5***	416.3***	426.6***	421.8***
		(69.2)	(65.1)	(69.2)	(68.3)	(66.0)	(68.6)	(67.1)	(72.8)
YSOC		16.2	-0.55	11.0	20.7*	15.6	16.8	21.6*	17.8
		(11.8)	(10.8)	(11.4)	(10.8)	(11.7)	(12.0)	(12.3)	(13.1)
Captive		-2.05***	-2.65***	-2.36***	-1.32***	-2.10***	-1.98***	-1.87***	-2.60***
		(0.48)	(0.47)	(0.46)	(0.46)	(0.47)	(0.48)	(0.46)	(0.68)
No originator rating		3.39**	2.55		4.70***	3.37**	3.40**	4.57***	2.72*
		(1.57)	(1.63)		(1.31)	(1.56)	(1.57)	(1.54)	(1.51)
Originator rating		0.11*	0.069		0.24***	0.11*	0.11*	0.16**	0.085
		(0.065)	(0.066)		(0.063)	(0.064)	(0.065)	(0.065)	(0.065)
Unemployment rate		-0.61	-0.75	-0.67	-0.52	-0.34	-0.60	-0.69	-0.73
		(0.80)	(0.81)	(0.81)	(0.75)	(0.74)	(0.80)	(0.78)	(0.78)
No servicer rating				1.45					
				(1.40)					
Servicer rating				0.031					
				(0.061)					
FC					2.43***				
					(0.64)				
Used car prices						-0.13**			
						(0.054)			
Small states							0.15		
							(0.40)		
Prefund								1.14**	
								(0.50)	
Pro-rata deal									-1.03*
									(0.59)
Relative WAL									-15.4
									(14.6)
Constant	8.70***	-0.49	-0.98	1.44	-4.08	12.2*	-0.64	-2.09	2.16
	(0.36)	(4.75)	(4.66)	(4.79)	(4.46)	(7.34)	(4.79)	(4.67)	(4.74)
Year issued FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	243	243	247	243	243	243	243	243	243
Adj. R^2	0.56	0.65	0.62	0.64	0.67	0.66	0.65	0.66	0.65
Number whole-loan tranches	41	41	45	41	41	41	41	41	41

Table 1.5: Ordered logit regressions of letter rating classes. The table shows results from ordered logit regressions of tranches from prime auto loan ABS deals issued between 2002 and 2007. Tranches are included if they are rated below triple-A, or if they are the triple-A rated tranche with the lowest seniority ranking in a deal. The dependent variable are tranches' issuance ratings, grouped and ordered as follows: BB = 1, BBB = 2,..., AAA = 5. Panel A reports odds ratios, with standard errors in parantheses. *, **, and *** denote statistical significance at the levels of 10, 5 and 1 percent, resp. Standard errors are clustered at the deal level, and allow for within-deal heteroskedasticity. Panel B reports differences in estimated probabilities of each outcome between whole-loan and originator deals, where probabilities are obtained as average over all observations.

Panel A.	(1)	(2)	(3)	(4)	(5)
Whole-loan tranche	0.31**	0.34**	0.35*	0.38	0.07***
	(0.15)	(0.18)	(0.22)	(0.25)	(0.06)
Hard c/e (target)	3.61***	4.04***	4.76***	4.81***	7.21***
	(0.63)	(0.77)	(0.90)	(0.90)	(2.45)
Excess spread	1.55**	1.83**	1.99**	1.99**	4.32***
	(0.32)	(0.44)	(0.53)	(0.54)	(1.99)
Previous losses	0.66***	0.65***	0.66***	0.66***	0.71***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
Coupon		0.93	0.98	0.99	1.41
		(0.08)	(0.24)	(0.24)	(0.47)
Original term		0.84***	0.74***	0.74***	0.63***
		(0.05)	(0.05)	(0.05)	(0.07)
Seasoning		1.03	1.16***	1.16***	1.45***
		(0.04)	(0.06)	(0.06)	(0.13)
Percent used			0.99	0.99	0.99
			(0.01)	(0.01)	(0.02)
YSOC			1.42	1.30	9.09
			(1.83)	(1.71)	(21.50)
Cap			1.17	1.08	0.02***
			(0.50)	(0.48)	(0.03)
No originator rating			2.45***	2.44***	2.05***
			(0.48)	(0.47)	(0.49)
Originator rating			1.42***	1.42***	1.23*
			(0.11)	(0.11)	(0.14)
Unemployment rate			1.24	1.19	0.53
			(1.44)	(1.40)	(0.68)
Pro-rata deal				0.79	
				(0.29)	
Relative WAL				1.34	
				(15.01)	
Issuance year FE	Yes	Yes	Yes	Yes	Yes
N	449	449	449	449	243
Pseudo-R^2	0.45	0.48	0.53	0.53	0.56
Number whole-loan tranches	56	56	56	56	41

Panel B.					
BB	0.033**	0.031**	0.029*	0.027	0.12***
BBB	0.054***	0.042**	0.035*	0.031	0.17***
A	0.023**	0.018*	0.013	0.013	-0.26***
AA	0.0021**	0.0019*	0.0014	0.0014	-0.025*
AAA	-0.11***	-0.093**	-0.079*	-0.072	

Table 1.6: Marginal effects for ordered logit regression. The table shows marginal effects of specification 3 in Table 1.5, which is an ordered logit regression of tranches from prime auto loan ABS deals issued between 2002 and 2007. Tranches are included if they are rated below triple-A, or if they are the triple-A rated tranche with the lowest seniority ranking in a deal. The dependent variable are tranches' issuance ratings, grouped and ordered as follows: BB = 1, BBB = 2,..., AAA = 5. For each covariate, I report the change in the estimated probability of being in each rating category for a unit increase in the covariate. I do not report values for the dummy indicating that the originator is not rated. In parentheses are t-statistics, and *, **, and *** denote statistical significance at the levels of 10, 5 and 1 percent, resp. Standard errors are clustered at the deal level, and allow for within-deal heteroskedasticity.

	BB	BBB	A	AA	AAA
Whole-loan tranche	.029*	.035*	.013	.001	-.079*
	(1.68)	(1.72)	(1.62)	(.98)	(-1.76)
Hard c/e (target)	-.043***	-.051***	-.019***	-.002	.116***
	(-10.02)	(-8.6)	(-2.7)	(-1.37)	(31.83)
Excess spread	-.019**	-.023***	-.009**	-.001	.051***
	(-2.6)	(-2.92)	(-2.41)	(-1.18)	(3.05)
Previous losses	.012***	.014***	.005**	.001	-.031***
	(7.19)	(8.43)	(2.23)	(1.45)	(-8.35)
Coupon	0	.001	0	0	-.001
	(.06)	(.06)	(.06)	(.07)	(-.06)
Original term	.008***	.01***	.004**	0	-.022***
	(4.51)	(4.13)	(2.4)	(1.31)	(-4.85)
Seasoning	-.004***	-.005**	-.002*	0	.011***
	(-2.86)	(-2.45)	(-1.92)	(-1.15)	(2.71)
Percent used	0	0	0	0	-.001
	(.65)	(.67)	(.61)	(.7)	(-.66)
Average loan size	-.007***	-.008***	-.003*	0	.017***
	(-3.33)	(-2.9)	(-1.81)	(-1.3)	(3.07)
YSOC	-.01	-.012	-.004	0	.026
	(-.27)	(-.27)	(-.27)	(-.26)	(.27)
Cap	-.004	-.005	-.002	0	.012
	(-.37)	(-.37)	(-.36)	(-.38)	(.37)
Originator rating	-.01***	-.011***	-.004*	0	.026***
	(-3.81)	(-4.35)	(-1.85)	(-1.42)	(3.9)
Unemployment rate	-.006	-.007	-.003	0	.016
	(-.18)	(-.18)	(-.18)	(-.18)	(.18)
Issuance year FE			Yes		
N			449		

Table 1.7: Spread regression of tranches rated below AAA. The table shows regressions of tranches from prime auto loan ABS deals issued between 2002 and June 2007. Tranches that carry at top rating of triple-A are excluded. The dependent variable is the issuance coupon spread, measured in percent. Standard errors are clustered at the deal level, and allow for within-deal heteroskedasticity. Standard errors are in parantheses, and *, **, and *** denote statistical significance at the levels of 10, 5 and 1 percent, resp. Equation 4 contains dummy variables for the rating groups A+, A-/A, BBB+, BBB-/BBB, BB+, and BB-/BB.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Whole-loan tranche	0.33***	0.29**	0.29**	0.22**	0.23**	0.19*	0.19*	0.41**	0.18**	0.17
	(0.12)	(0.11)	(0.12)	(0.10)	(0.11)	(0.096)	(0.099)	(0.16)	(0.069)	(0.10)
A	-0.11*	-0.022	-0.021		-0.021	-0.011	-0.034	-0.022	-0.092*	0.024
	(0.058)	(0.057)	(0.095)		(0.062)	(0.069)	(0.067)	(0.057)	(0.052)	(0.049)
BBB	0.42***	0.53***	0.54***		0.52***	0.53***	0.49***	0.53***	0.45***	0.58***
	(0.070)	(0.074)	(0.12)		(0.079)	(0.083)	(0.080)	(0.074)	(0.067)	(0.067)
BB	2.19***	2.30***	2.29***		2.28***	2.28***	2.24***	2.29***		
	(0.15)	(0.17)	(0.19)		(0.17)	(0.18)	(0.17)	(0.17)		
Slope yield curve		-0.019	0.0066	0.0035	-0.052	-0.035	-0.019	-0.030		-0.035
		(0.065)	(0.079)	(0.064)	(0.065)	(0.067)	(0.070)	(0.065)		(0.055)
Corporate bond spread		0.65***	0.78***	0.65***	0.57***	0.25	0.52***	0.64***		0.53***
		(0.19)	(0.22)	(0.18)	(0.19)	(0.16)	(0.16)	(0.18)		(0.16)
Captive		0.17**	0.15*	0.18**	0.15*	0.14	0.17**	0.16*		0.21***
		(0.080)	(0.088)	(0.067)	(0.083)	(0.086)	(0.082)	(0.082)		(0.053)
FC		0.24***		0.23***	0.21***	0.14**	0.086	0.28***		0.18***
		(0.070)		(0.069)	(0.070)	(0.067)	(0.070)	(0.075)		(0.066)
Deal Size		-0.038	-0.0054	-0.061	-0.065	-0.093	-0.11	-0.0053		-0.094**
		(0.065)	(0.083)	(0.061)	(0.067)	(0.072)	(0.068)	(0.067)		(0.046)
New deal		0.10	0.13	0.12	0.091	0.044	0.032	0.076		0.059
		(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.13)		(0.11)
Pro-rata deal		0.055	0.047	0.024	-0.17*	-0.22**	0.46**	0.081		0.033
		(0.062)	(0.075)	(0.059)	(0.10)	(0.10)	(0.18)	(0.063)		(0.055)
WAL					-0.14***	-0.095*	-0.13***			
					(0.051)	(0.050)	(0.046)			
Matched Treasury rate						-0.28***				
						(0.089)				
Matched T rate × Pro-rata							-0.20***			
							(0.052)			
Multiple originators								-0.21		
								(0.17)		
Constant	0.53***	-1.04**	-1.35**	-1.08**	-0.26	1.10**	-0.26	-1.02**	0.55***	-0.72*
	(0.072)	(0.48)	(0.57)	(0.45)	(0.51)	(0.50)	(0.48)	(0.45)	(0.064)	(0.38)
Year issued FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	222	222	177	222	222	222	222	222	194	194
Adj. R^2	0.79	0.81	0.82	0.82	0.82	0.83	0.83	0.82	0.56	0.65
Number whole-loan tranches	40	40	40	40	40	40	40	40	31	31

Table 1.8: Spread regression of AAA-rated tranches. The table shows regressions of triple-A tranches from prime auto loan ABS deals issued between 2002 and June 2007. The dependent variable is the issuance coupon spread, measured in basis points. Specifications 1, 2, 3, 4, 6, and 8 only contain the triple-A rated tranche with the lowest seniority ranking from each deal. Specification 3 only contains tranches from deals with bank or captive collateral. Standard errors are clustered at the deal level, and allow for within-deal heteroskedasticity. Standard errors are in parantheses, and *, **, and *** denote statistical significance at the levels of 10, 5 and 1 percent, resp.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Whole loan tranche	-0.96	-6.30	-5.61	-5.53	0.44	-2.84	1.27	-6.02	2.36
	(4.65)	(6.48)	(6.63)	(6.52)	(4.02)	(4.86)	(3.21)	(5.73)	(2.61)
Hard c/e (target)		105.8	9.76	109.1	0.91			143.2	
		(84.9)	(106.3)	(83.9)	(9.21)			(89.2)	
Excess spread		1.90	0.80	1.88	0.47			1.98	
		(1.85)	(2.03)	(1.84)	(1.19)			(1.70)	
Coupon		-2.36	-1.12	-2.54	-0.038			-1.79	-0.32
		(2.02)	(2.18)	(2.03)	(1.35)			(1.83)	(0.59)
Original term		0.26	0.33	0.19	0.24			0.23	
		(0.50)	(0.61)	(0.50)	(0.33)			(0.49)	
Seasoning		0.044	-0.17	-0.12	-0.015			-0.092	
		(0.50)	(0.52)	(0.50)	(0.30)			(0.48)	
Percent used		0.026	0.037	0.011	-0.020			0.030	
		(0.091)	(0.13)	(0.092)	(0.064)			(0.082)	
Average loan size		-78.1	-476.6	-88.1	44.1			82.3	
		(790.5)	(859.2)	(798.7)	(525.0)			(708.5)	
YSOC		-103.1	-86.9	-119.9	44.3			-93.8	
		(106.9)	(109.6)	(109.0)	(78.3)			(97.2)	
Captive		-3.15	-2.47	-3.40	-3.57	0.19	-0.64	-1.06	0.11
		(4.34)	(4.73)	(4.36)	(3.13)	(3.07)	(2.49)	(4.18)	(2.22)
FC		-6.88		-7.36	-3.51	2.60	2.75	-6.34	3.17
		(9.43)		(9.41)	(5.77)	(4.25)	(2.91)	(9.29)	(2.98)
Previous losses		-1.51	1.35	-1.48	-1.75			-3.18	
		(5.50)	(5.69)	(5.54)	(3.16)			(5.02)	
No originator rating		-9.29	0	-9.66	-8.75			0.75	
		(17.1)	(.)	(17.0)	(10.2)			(17.7)	
Originator rating		-0.81	-1.22	-0.86	-0.66			-0.38	
		(0.82)	(0.97)	(0.82)	(0.50)			(0.84)	
Unemployment rate		-8.73	-6.41	-9.09	-7.66				
		(9.29)	(10.1)	(9.40)	(6.62)				
WAL				-4.98	5.10***		4.97***		4.89***
				(5.16)	(1.87)		(0.46)		(0.46)
Slope yield curve						-10.6***	-5.72**	-10.3***	
						(3.09)	(2.46)	(3.13)	
Corporate bond spread						6.02	-0.34	5.87	
						(7.42)	(5.70)	(7.33)	
Deal Size						-0.75	2.09	2.51	
						(3.24)	(2.32)	(4.39)	
New Deal						3.62	2.07	4.25	
						(5.03)	(3.82)	(4.99)	
Pro-rata deal						-2.43	-1.35	-2.23	
						(2.27)	(1.88)	(2.73)	
Constant	40.7***	108.8*	114.8*	130.7**	82.0**	53.2***	34.6***	56.2*	23.1***
	(2.70)	(57.5)	(64.3)	(64.1)	(39.2)	(13.9)	(10.8)	(32.2)	(2.65)
Issuance year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	174	173	149	173	549	174	553	173	550
Adj. R^2	0.22	0.22	0.23	0.22	0.32	0.29	0.32	0.29	0.31
Number whole-loan obs	14	14	14	14	47	14	48	14	48

Chapter 2

The cross section of expected auto loan ABS returns

2.1 Introduction

Securitization is the practice of pooling the cashflows of a large number of financial assets and structuring them so as to create a much smaller number of tradable securities. The technique was pioneered by Fannie Mae in 1970 for agency mortgage loans, and is now used for virtually all classes of debt. The widespread adoption of securitization as a financing technique is often regarded as one of the major transformations of the US and global financial systems in recent decades. The total volume of securitized debt outstanding in the US, excluding CDOs, was \$10 trillion at the end of 2014, compared to \$7.8 trillion in US corporate bonds ([76, 77, 78]).

This paper investigates secondary market pricing of a particular class of securitized debt, namely auto loan asset-backed securities (ABS). Along with credit card debt, car loans form the most established collateral class for consumer credit securitization in the United States. The first auto loan ABS were issued in 1985, after which the market saw rapid growth, and at the end of 2006 there were securities with a principal volume of \$134.4 billion outstanding ([75]). During the financial crisis, spreads increased for all classes of private securitized debt and issuance volumes dropped, but auto loan ABS were among those least affected. Since 2010, auto-related ABS, the majority of which are backed by auto loans, have been the strongest-issuing US ABS segment ([68]), and auto loan ABS have become the benchmark sector for consumer ABS

([84]). However, despite its size and importance, this market has hardly been studied from an asset-pricing perspective.

Using a comprehensive dataset of secondary market tranche prices covering the period December 1994 to April 2007, I study the cross section of expected returns of US auto loan ABS. As determinants of expected monthly excess returns over the risk-free rate[1] I consider factor loadings and security characteristics. Motivated by the standard two-factor model for corporate bonds of [39], my systematic risk factors are an interest rate factor of Treasury returns, and several non-interest rate factors using auto loan ABS portfolio returns. As alternative measures of security risk I use tranches' weighted average life (WAL), which is the standard measure of time to maturity in this market, and their credit ratings. I investigate if the risk factors are priced in the cross section of returns on individual securities, and in particular test whether results are robust to the inclusion of characteristics as control variables. The theoretical paradigm of asset pricing is that expected security returns are compensation for bearing systematic risk which is measured by comovement of security returns with systematic factors, and "the proper betas should drive out any characteristics in cross-sectional regressions" ([24]). In my analysis, I take a more agnostic standpoint, considering betas and characteristics as equally valid determinants of expected returns, an approach that has been advocated by e.g. [23]. In particular, I will not interpret effects of security attributes controlling for factor exposure as mispricing. My focus is not on whether factors drive out risk characteristics *entirely*, but on whether betas have *any* significance for expected returns when controlling for the effects of characteristics.

[1] Throughout this paper, the term "1-month risk-free rate" (or simply "risk-free rate") refers to the return on a 30-day Treasury bill.

The empirical approaches I follow are portfolio sorts, Fama-MacBeth regressions, and panel regressions. All of these use betas estimated in rolling regressions of 24 months length, which result in 14316 tranche-month observations of betas and next-period returns spanning the period 12/96 to 04/07. Sorting assets into portfolios every month I obtain estimates of factor risk premia, that is, average excess returns of high-beta over low-beta securities, which I find to be positive for a number of factors. However, due to data limitations, I am not able to simultaneously investigate competing effects of betas and characteristics on expected returns using portfolio sorts. Robustness to the inclusion of observable security characteristics is the most important check for factor pricing results, since they contain similar risk information and thus are possible alternative drivers of expected returns (e.g. [46]). Both regression approaches that I employ allow for including the two covariate groups jointly.

I find an interest rate risk factor TERM, defined as the excess return on a 5-year Treasury security over the risk-free rate, to be significantly priced in auto loan ABS returns. It generates a univariate risk premium of 5 basis points (bps) per month, and produces significant return differentials between high- and low-exposure portfolios in bivariate sorts. Furthermore, the interest rate beta is significantly positively related to excess returns in Fama-MacBeth regressions that only include betas and no characteristics, as well as when controlling for ratings. However, when allowing for WAL as simultaneous determinant of expected returns in regressions, the positive effect of interest rate beta disappears. Panel regressions confirm the TERM beta coefficient signs found previously, but results are hardly significant.

Regarding pricing of systematic non-interest rate risk, I find that a factor AutoLH, defined as the excess return of lower-rated tranches over top-rated ones, plays an important role for expected returns. The same is true, even though to a lesser extent, for a factor AutoLow, defined as the excess return of lower-rated tranches over Treasuries. On the other hand, factors involving either tranches of all rating categories, or only those rated AAA,[2] do not play a role for pricing. The factors AutoLH and AutoLow, both of which rely on returns only from tranches rated below AAA to capture realizations of systematic risk, generate significantly positive average slope estimates in Fama-MacBeth regressions, as well as highly significant coefficients in panel regressions. This is the case even when controlling for both tranches' time to maturity and ratings as competing determinants of expected returns. While coefficient estimates are generally similar, the overall evidence is stronger for the factor of return differentials between lower- and top-rated tranches, AutoLH. It is significant in a larger share of Fama-MacBeth regressions, and evidence of its pricing is furthermore more convincing in portfolio sorts. Univariately, AutoLH produces risk premia of 4-5 bps, and it generates significant portfolio return differences in bivariate sorts. On the other hand, AutoLow does not produce a significant risk premium in univariate sorts, and the bivariate sorting evidence is not consistent across sorting procedures.

The only existing academic evidence on the pricing of auto loan ABS is provided by studies that investigate determinants of issuance spreads on securitized debt where these assets are always only part of a larger data set ([14], [37], [41], [35], [83]). In particular, secondary market pricing of US car loan ABS, which is the subject of this article, has not been studied in the literature before. I am taking the most common approach of the asset pricing literature dealing with secondary market prices, which is to study the relationship between expected return and risk captured by systematic factors. While such analysis is abundant for stocks (e.g. [22]), and also available for e.g. corporate bonds and hedge fund shares ([10]), to my knowledge only three studies

[2]Throughout this paper, I will use "AAA" to refer to a maximal average rating (as explained in section 2.4.2 from the three rating agencies Fitch, Standard & Poor's, or Moody's, even though only the former two use this symbol. The top rating from Moody's is "Aaa".

in this vein exist for any classes of securitized debt. [70] study the cross section of ABS spreads for Manufactured Housing ABS and for Home-Equity Loan ABS during crisis periods, and [15] as well as more recently [16] study the cross section of agency mortgage-backed securities. However, none of these three follow any of the approaches that I use. In the absence of papers providing results directly comparable to mine for other securitized debt, my main point of reference is the literature on corporate bonds as another fixed-income class.

[46] study the US investment-grade corporate bond market during the period 1973 to 1996. They find in univariate sorts into quintile portfolios that a factor of corporate bond excess returns over Treasuries generates a statistically significant risk premium of 13 bps per month. This number is much larger than the risk premia of 4-5 bps that I find for factors of auto loan ABS returns. However, the corporate bond returns in [46] are larger in magnitude than the returns in this paper. Their risk premium arises as the difference between average portfolio returns of 0.35 percent and 0.21 percent, whereas my high-beta and low-beta portfolios on average return only 0.13 and 0.08 percent, respectively. Thus relative to return size my Auto factor risk premia seem quite comparable. Regarding the interest rate factor, in contrast to my finding that TERM is significantly priced, [46] find that in univariate sorts an interest factor like the one I use produces no statistically significant risk premium. In Fama-MacBeth regressions controlling for bond time to maturity, [46] find, like me, that term beta is not a significant determinant of expected returns. However in contrast to them, my measure of maturity is highly significant in the presence of interest rate betas.

The remainder of this paper is organized as follows. In the next section I introduce asset-backed securities of auto loans, and in particular discuss the different risks these assets carry. Section 2.3 presents the data I use, discusses relevant financial economic theory, and lays out my empirical approaches. Section 2.4 contains definitions of my variables. Section 2.5 presents results from the time series regressions in which betas are estimated, as well as describes the resulting data set of tranche-months observations of factor loadings and returns. The empirical results are in section 2.6 for portfolio sorts, and in section 2.7 for Fama-MacBeth and panel regressions. Section 2.8 concludes.

2.2 Primer on auto loan ABS and their risks

In a car loan securitization, the sponsor[3] of the transaction (usually referred to as a "deal") initially owns the loans to be securitized, which they have either originated themselves or bought from other companies. The collateral generally consists of plain-vanilla recourse auto instalment loans to individuals. They are transferred to a special purpose entity (SPE) created specifically for the deal in question, which then sells debt securities called tranches to investors. The SPE is bankruptcy-remote from the sponsor's business, and the tranches are backed by the SPE's assets only. The latter consist primarily of the loans, but in addition there may be other resources available to the SPE and thus supporting the tranches.

Tranches are usually amortizing bonds without a fixed repayment schedule. The basic cashflow mechanics of an auto loan ABS transaction are that pool receipts during a collection period (usually of length a month) are shortly afterwards distributed as principal and interest payments to tranche holders. The precise allocation of pool collections mechanically follows from the deal's so-called structure, which is laid out in deal documents. The structure is a prescription of cashflow streams covering all possible events, with the only discretionary feature generally being a call option on the

[3]The SEC defines sponsor as follows: "Sponsor means the person who organizes and initiates an asset-backed securities transaction by selling or transferring assets, either directly or indirectly, including through an affiliate, to the issuing entity." (17 CFR 229.1101)

part of the SPE. Given that late payments and defaults, but also prepayments occur for car loans, the precise amounts of monthly pool principal and interest collections are subject to uncertainty. As a consequence, tranches do not have fixed cashflow schedules, any deviation from which would constitute an event of default.

The characteristic feature, and often principal purpose, of securitization is that by structuring cashflows, claims to the same underlying assets are created that have new risk and cost characteristics. The basic idea is to create tranches of different riskiness by introducing a seniority ordering, according to which more senior tranches are paid down first, so that losses first apply to less senior tranches. This general cashflow scheme is referred to as "waterfall". In its pure form, only the senior-most tranche receives principal in a period, while all tranches with remaining principal outstanding are paid interest. For subordinate tranches it can take years for principal to begin paying down. In practice, deal structures exhibit deviations from the basic waterfall scheme just described, but for the deals in my sample it is always at the core, resulting in the transformation of a homogenous loan pool into many very safe claims, and a few more risky ones. This results in lower overall funding costs.

Credit enhancements are all features of a deal that play a role for reducing the credit risk of securities created. Subordination via time tranching as just described is a principal means of credit enhancement. Others forms include overcollateralization,[4] excess spread,[5] reserve accounts,[6] and letters of credit from third parties. Finally, an important credit enhancement are financial guarantees by bond insurers. In so-called

[4]Overcollateralization refers to an excess in pool principal balance over the total principal amount of tranches sold. This difference is available to absorb pool losses before tranches are affected.

[5]Excess spread refers to an excess in predicted pool interest receipts over and above what is required for tranche interest payments. Differences can be collected in an account with the SPE, and be available to cover pool losses.

[6]In a reserve account, a sponsor may deposit cash when the tranches are issued. These funds are then available to support tranche holders' claims.

“wrapped deals”, both principal and interest payments on all but, or even including the most subordinated tranches are insured against default after all other SPE rescources have been exhausted.

2.2.1 Risks of auto loan ABS

In this section, I discuss the various types of risk that investors in auto loan ABS securities face, and which thus possibly play a role for pricing.

Interest rate risk

Most auto loan ABS tranches carry a fixed coupon, and all securities in my sample do. As a result, their prices are strongly affected by fluctuations of benchmark Treasury interest rates. The pricing measures quoted and followed by market participants are yield spreads.

Credit risk

In practice, every pool of car loans experiences losses. Since tranches are principally backed by the cashflows from the underlying loans, they carry default risk. Specifically, this is the credit risk that receipts from the pool, even supported by other available credit enhancements, will not be sufficient to fully satisfy tranche holders’ claims. In the case of tranches that are supported by a bond insurance policy, the insurer must fail to make good on his obligations for a credit event to occur. Such insurance risk is discussed below in section 2.2.1.

The historical credit performance for the universe of US auto loan ABS tranches is characterized by very few losses. I rely on data provided by Moody’s and Standard&Poor’s about the securities they rated. The resulting numbers are representative, since virtually all auto loan ABS tranches were rated by at least one of these agencies. During the period 1993-2012, the probability for a tranche rated by Moody's to be materially impaired[7] over its lifetime was 0.3% by security count, and less than 0.05% by dollar volume. During that period, there were 14 cases of material impairment, and in only two cases tranche holders incurred losses. 11 impairments happened up until 2002, at least 9 of which involved subprime tranches. There were no impairments between 2003 and 2006. [80] reports that of the approximately 1,900 auto ABS tranches they ever rated only two have defaulted, one in 1998 and another in 2002. Both were subordinated bonds originally rated BB, and they came from separate subprime transactions. For the period since the financial crisis started in 2007, Moody's has had two rated subprime tranches be resolved in 2007 with loss-given-default rates of 13 and 2 percent, and another case of impairment happened in 2009. For S&P, the available information is that auto loan ABS default rates for the years 2010 and 2011 were 0.14 and 0.76 percent, respectively, but no losses occured ([81]).

In summary, losses on auto loan ABS tranches are very rare, and in the past have only occurred for tranches from subprime deals. In light of this almost flawless historical performance, it is natural to ask to what extent auto loan ABS tranches are perceived by investors to carry credit risk. One principal indication that this is indeed the case are credit ratings, whose specific aim is to assess the amount of credit risk that securities carry. There is considerable ratings variation, with grades of BBB not uncommon for subordinate securities, even though most tranches carry the maximum rating of AAA. From published rating methodologies it is clear that servicer risk, prepayment risk, and insurance risk also play a role for the rating process, and I will touch upon the relation of those categories to credit risk in the next sections.

[7] Material impairment is defined as a security "sustaining a payment shortfall that remains uncured, or that has been downgraded to Ca or C" ([65]).

Furthermore, subprime auto loan ABS are characterized by industry participants as one of the "more credit sensitive sectors" ([67]).

Payment timing risk and prepayment risk

Auto loan ABS tranches, as explained above, do not have a fixed cashflow schedule, any payment retardation from which would constitute a case of default. Payment timing risk refers to the uncertainty of investors about the exact timing and corresponding amounts of cashflows. This uncertainty exists mainly regarding principal amortization, since interest due is a specific amount in each month, derived from principal outstanding and the applicable coupon, that is very unlikely to be missed due to its high within-month priority rank out of pool collections.

Variation over time of auto loan pool collections mainly occurs for two types of reasons. On the one hand, defaults and delinquencies slow down amortization. On the other hand, repossessions and accidents generally result in earlier collections and faster pool amortization. However, despite these sources of variation, auto loan pool repayments are viewed as "fairly predictable" ([36]), and investors appreciate the "stable average lifes of auto loan ABS" ([34]). Importantly, the classical prepayment issue of mortgage pools, namely that much prepayment occurs as a result of refinancing, which in turn is to a large extent driven by interest rates, is not present for car loans ([36]). Both resale before the term of the loan, as well as refinancing, virtually do not occur ([53]). As a result, prepayment levels are low relative to mortgage pools, and prepayment risk, that is, the risk of foregoing interest payments due to early amortization, is less of an issue for auto loan ABS.

Payment timing predictions and stress scenarioes play a role for rating agency risk analysis, since the faster a loan pool pays down, the fewer excess spread interest payments are available as buffer to avoid principal losses ([43], [80]).

Servicer risk

The servicer of an auto loan ABS pool is the agent responsible for managing accounts and processing payments. This role is often taken on by the deal sponsor or an affiliate, but sometimes the loan originator, or a third party company, are contracted. Servicing fees generally range from 0.75%-1% for prime quality pools, and up to 3.5% for subprime pools ([79]). Importantly, the servicer is responsible for collections, and in particular for dealing with delinquent borrowers and managing defaults. As a result, the servicer's performance directly affects pool losses as well as cashflow timing.

Servicer risk refers to tranche cashflow variation that is due to the behavior of the servicer. This can occur e.g. due to ineffective servicing guidelines or insufficient capacities. For example, a servicer can decide to cut its payroll at the cost of reduced collection efforts. In particular for subprime deals this can matter substantially for loss levels, since for higher-risk borrowers an active collection strategy may be necessary to minimize loss levels. Such a measure will often be the result of business problems of the servicer, so that the underlying risk factor is its financial condition. In extreme cases, the servicer may also be replaced by another company. Such a servicer transfer is generally seen as very costly to investors, since both the short-term and long-term effects on collections are uncertain. The designation of a back-up servicer can mitigate this problem.

Due to its pivotal role for pool collections, servicer risk is related to both credit risk and prepayment risk. Rating agencies put much emphasis on the servicer for their assessments, and frequently mention its quality and stability as an important factor for a rating issued. They also require historical loan performance statistics to be from the same servicer, if that is possible.

Liquidity risk

Auto loan ABS are traded in an over-the-counter (OTC) telephone market of institutional agents, where liquidity is a major issue. Given the absence of a unified market place, a seller has to locate a buyer and they need to agree on a price. This may take time, and the seller may be forced to accept a discount in the form of a difference between the transaction price and the asset's fundamental value ([19]). Market liquidity, that is the ease with which an asset is traded ([19]), is of particular concern in OTC markets.[8] Liquidity risk refers to the uncertainty of an investor about the liquidity situation they will encounter if they wish to sell the security at a later point in time, and thus the uncertainty about the discount they will face. Market liquidity of an asset is a function of the general properties of the asset's market, which determine a general expected liquidity level, as well as of current events. Episodes of extreme declines in market liquidity of certain assets are observed periodically.

Insurance risk

A substantial fraction of auto loan ABS tranches are covered by a bond insurance policy, under which payments of principal and interest are guaranteed in full. Insurance risk thus refers to the possibility that pool payments and any other cash resources of the SPE are depleted, and in addition the bond insurer defaults on the policy. In the majority of cases, the underwriter is one of the large monoline insurers. During my sample period, all of these carried a AAA rating, and bond insurance was often used as primary form of credit enhancement by subprime auto issuers ([28]).

[8] [27] (p. 199) discuss the case of OTC-traded corporate bonds.

Option risk

Almost all auto loan ABS deals include a call provision that allows the servicer to buy back all outstanding tranches once the pool principal has reached a given fraction of its original value, where the value of this fraction varies between 2 and 20 percent. As a result, investors face uncertainty regarding the length of the period over which they will receive interest. However, in practice servicers generally execute the call option at the earliest point possible, so that the actual amount of option risk seems limited.

2.3 Data and empiricial methodology

I now introduce the dataset on US auto loan ABS used in this study. At its core are monthly return time series of individual tranches covering the period 12/94 to 04/07. Section 2.3.2 gives an overview of the theoretical literature on the determination of expected returns, and section 2.3.3 explains the empirical approaches I follow.

2.3.1 Data

The object of this study is the universe of US auto loan ABS, where I limit my attention to the time before the financial crisis that started in 2007. All securitization markets underwent a period of unprecedented volatility and uncertainty, caused by rising subprime mortgage defaults and losses on related structured finance securities that led to a general scepticism about the risks of securitized debt. I think of the period before the crisis as showing the market functioning under "normal" conditions.

I start from a list of all securities on the Bloomberg system classified as auto ABS, and issued in the US in US dollars between January 1990 and April 2007. For each deal included, I determine the collateral type using Bloomberg descriptions, along with information from rating agency websites and web searches. I only consider securities backed by pools of auto instalment loans ("auto loan ABS tranches"), and exclude all other collateral types such as leases or dealer floorplans. Some tranches are listed multiple times on Bloomberg with different properties regarding allowed investor base and security registration. In each case I only keep the version eligible for trading exemption under rule 144a of the Securities Act. I only include deals in my sample that use a so-called owner trust structure, which allows for the flexibility in pool cashflow allocations necessary for the waterfall structure described above, and exclude grantor trusts, which do not allow for time tranching ([74]) and were mainly used in the earlier days of auto loan securitization. I furthermore do not include master trusts, which are particularly suited for revolving-credit securitizations, or synthetic deals. Finally, I exclude deals where all tranches pay principal as soft bullets (meaning principal is amortized at once, but at an uncertain date), and tranches that are either interest-only, or have an original principal balance or a coupon rate of zero.

My main variable of interest is the monthly tranche return. I restrict my sample further to only include tranches that pay a fixed coupon using the 30/360 day count convention at a monthly frequency. This excludes fixed-coupon tranches using the convention Act/360, which are mostly very senior tranches (classes A1 and A2) with short maturities, and about 150 floating-rate tranches, as well as tranches with a "step" provision for a coupon change. Furthermore, I require tranches to have a rating history, and that their cashflows do not show any irregularities in the data. I calculate the net holding period return between the ends of months $t-1$ and t in percent as

$$R_t = 100 \times \left(\frac{q_t B_t + P_t + I_t + AI_t}{q_{t-1} B_{t-1} + AI_{t-1}} - 1 \right),$$

where q is the clean end-of-month price (as a fraction of face value), B is the tranche balance outstanding at the end of the month, P and I are principal and interest cashflows received during the month, and AI is the interest accrued between the nominal payment day of the tranche and the end of the month. Returns are calculated under the assumption that principal and interest are not reinvested between their payment date and the end of the month. All cashflow and other data used in this calculation are obtained from Bloomberg. End-of-month prices are from the Bloomberg Generic pricing source, which is a consensus valuation formed using quotes from contributing dealers.

An important characteristic of an auto loan ABS tranche at a point in time is its expected weighted average life (WAL), which is the standard measure of time to maturity in securitized debt markets. WAL is defined as the average time until receipt of outstanding principal, where times are weighted by the respective principal payment amounts. In practice, market participants form real-time expectations about outstanding tranches' WALs using pool cashflow models. Such ex-ante data is not available to me. In my empirical analysis, I use tranches' realized ex-post WALs as approximation for expected ex-ante values. This is possible since all tranches in my sample have been paid off by now,[9] and it is sensible since, as I have explained above in section 2.2.1, cashflows of auto loan pools are regarded to be very predictable. Furthermore, much of my analysis is cross-sectional in nature, comparing returns within a period, so that common errors in the ex-post WAL approximation do not play an important role. Pool paydown speeds are affected by systematic events, so that behavior across tranches is expected to be correlated. I only consider return observations for securities with a WAL of at least three months, a restriction that is common in the literature, e.g. to avoid pricing errors due to low trading volume and liquidity (e.g. [60]). My final data set consists of 45,378 period-return observations

[9] I test if the original tranche principal balance agrees with the sum of reported individual repayments, and exclude 8 tranches because of deviations of more than 0.005 percent.

with corresponding WAL and rating during the period 12/94 to 04/07 from 1299 tranches in 580 deals.

Table 2.1 shows distributions of monthly tranche returns in excess of the 1-month risk-free rate. For the remainder of the paper, "return" always refers to this excess return. In Panel A I report statistics for all observations, as well as separately for returns from top-rated tranches and for those rated below AAA. The overall mean return is 13.7 bps, with a standard deviation of 62.3 bps, and the distribution is left-skewed, meaning that negative outliers are more important. Return distributions for the two rating groups differ with respect to mean and standard deviation, but both are left-skewed. Top-rated tranche returns, which account for over three quarters of observations, have a significantly lower average return than lower-rated ones, at 12.1 versus 18.2 bps. Furthermore, I document in Panel B of Table 2.1 return distributions omitting monthly observations in excess of the risk-free rate that are larger than 5 percent or smaller than -5 percent. This procedure eliminates 47 observations, all of which come from tranches rated below AAA. Throughout the rest of this paper, I use this cut excess return sample in order to avoid results being dominated by outliers, following [54].

2.3.2 Theories of expected returns

The aim of this study is to understand market pricing of auto loan ABS. The object of study in this context is the holding period return an investor is anticipating, when buying an asset, to realize over a given horizon (usually a month or a year) into the future, in excess of a benchmark return. Expected returns are not directly observable, an issue I will discuss below. Oftentimes the benchmark is the risk-free return that can be obtained over the same horizon by buying a government or other risk-free security maturing at the end of the holding period. A major advantage of expected excess return as a pricing measure is that it is readily comparable across assets.

One of the fundamental issues in asset pricing is to explain expected returns, and a number of theories have been brought forward aiming at explaining why some assets have higher expected returns than others. The most prominent ones are the Capital Asset Pricing Model (CAPM), the Intertemporal CAPM (ICAPM) of [62], the Arbitrage Pricing Theory (APT) of [73], and the Consumption CAPM (CCAPM) of [17]. The general insight of these models is that assets with more systematic risk have higher expected returns, the logic being that investors will be rewarded (through higher expected return) only for bearing *systematic* risk, since idiosyncratic risk can be effectively minimized by holding (perfectly) diversified portfolios. Even though these theories differ substantially regarding their underlying derivations, they all have in common both the logic used to measure systematic risk, and the form of the theoretical relationship between risk and expected return that is derived. Roughly speaking, systematic risk is measured as the comovement of an asset's return with certain variables called *systematic risk factors*. Specifically, let $f = (1, f^1, \ldots, f^J)'$ be a column vector of such variables, with a 1 added. Then the *exposure* of asset i to factor f^j, called β^{ij}, is given by the $(j+1)$th element of the row vector of coefficients from the regression

$$R^i_\tau = \sum_j \beta^{ij} f^j_\tau + \epsilon^i_\tau$$

of the excess return of asset i, R^i, on the risk factors. Specifically, we have

$$\beta^{ij} = Var(f)^{-1} Cov(f, R^i),$$

assuming that factors and returns are stationary over the estimation period in question. The term "regression coefficient" is used in a population sense here. According to all of the above theories, expected excess returns are then linearly related to exposures by the equation

$$E(R^i_{t+1}) = \sum_j \lambda^j_t \beta^{ij}_t, \tag{2.1}$$

where the λ^j are parameters called the *market prices of risk* taht can vary over time.[10] But even though this result is common to all models, they differ with respect to their view of what systematic factors are or should be. The CAPM has as single systematic factor the return on the total wealth portfolio. The ICAPM, which is a generalization of the CAPM, additionally includes state variables that predict changes in the investment opportunity set ([24], pp. 166/167). The APT criterion for factor inclusion is that they "characterize common movement" of asset returns ([24], p. 182). In the CCAPM, aggregate consumption growth is the only risk factor.

In all of the theories expected return is solely determined by betas as in the above equation. This implies in particular that security characteristics should have no ability to explain expected returns when controlling for the effects of betas. Characteristics should be dominated by betas in regressions ([24], who argues (p. 79) that what matters is "how you behave, not who you are"). The question how betas fare against characteristics in explaining expected returns has generated an active literature. A seminal paper for corporate bonds is [46], who find that a market risk factor has explanatory power for expected returns controlling for characteristics, but yield-to-maturity is not driven out by betas. A recent paper for stocks is [23], who say that "while some researchers are inclined to view expected return variation associated with factor loadings (betas) as due to risk, and variation captured by characteristics like

[10] Modern asset pricing theory, starting from the basic equations

$$p_t = E(m_{t+1} x_{t+1}), \quad m = f(data),$$

([24], p. 44) accomodates all the above linear factor models as special cases.

book-to-market as due to mispricing, we believe that a more agnostic perspective on this issue is appropriate.” My work is in this agnostic spirit.

2.3.3 Beta estimation and empirical approaches

I employ multiple approaches to investigate the roles of betas and characteristics for expected tranche excess returns. I begin in section 2.6 with portfolio sorts, and section 2.7 then presents results from two different regression setups, Fama-MacBeth regressions and panel regressions. Throughout, I will work with monthly excess returns over the 1-month risk-free rate, denoted by R. All approaches have in common that they aim at establishing a relationship between security attributes (betas and characteristics) known at the beginning of a holding period, that then can be interpreted as explaining expected returns, and subsequent returns over the period. Given the unobservability of the latter, this is a common way of identifying determinants of expected returns. The strategy is to show predictive ability of pre-determined attributes, since in efficient financial markets predictable returns should be reward for higher risk, and predictors thus measure of priced risk.

The first step for all approaches is to estimate tranche exposures to systematic risk factors in time series regressions. This is done in so-called rolling regressions, where a new beta is estimated for each period of 24 months length. The betas estimated in the rolling period ending with period t are then used as predictors for the next-period return R_{t+1}. For the purpose of exposition, let $f^1, \ldots, f^J$ be the J systematic factors in a factor model. For each security i that has a return observation R^i_{t+1}, and that has returns in at least 21 months between $t-23$ and t, I run the regression

$$R^i_{t-\tau} = \alpha^i + \sum_j \beta^{ij}_t f^j_{t-\tau} + \epsilon^i_{t-\tau}, \quad \tau = 0, \ldots, 23. \tag{2.2}$$

I obtain estimates $\hat{\beta}_t^{ij}$ for all securities i and all factors f^j and for each rolling period ending at t where a rolling regression is run.

In portfolio sorts, the beta estimates are used to sort tranches into quantile portfolios every month, and then portfolio returns in the subsequent period are observed. I go into more detail in section 2.6. In the classical regression setup following [40], second-stage cross-sectional regressions are run every period, and then time series averages of the slope coefficients are calculated. Specifically, for every period t where estimates $\hat{\beta}_t^{ij}$ are available for at least 15 tranches, I run a cross-sectional predictive regression of next-period returns on betas and characteristics,

$$R_{t+1}^i = \gamma_t^0 + \sum_j \gamma_t^j \hat{\beta}_t^{ij} + \sum_k \delta_t^k c_t^{ik} + \eta_t^i, \quad i = 1, \ldots, I_t, \tag{2.3}$$

where the c_t^{ik} are characteristics of tranche i at time t. These regressions yield time series for the predictive slope estimates $\hat{\gamma}_t^j$ and $\hat{\delta}_t^k$ for all factors f^j and all characteristics c^k. In the third stage of the Fama-MacBeth methodology, average values $\bar{\hat{\gamma}}^j$ and $\bar{\hat{\delta}}^k$ of those time series are then obtained, and tested against zero. If an average slope coefficient is significantly different from zero, it means that the corresponding factor beta or characteristic has predictive power for excess returns, and is thus a determinant of expected returns. [59] shows for stocks that averages of Fama-MacBeth coefficients indeed have strong predictive power for returns. In the panel regressions, all observations of betas, characteristics, and subseqent returns are pooled to estimate the predictive equation

$$R_{t+1}^i = \gamma_t^0 + \sum_j \gamma_t^j \hat{\beta}_t^{ij} + \sum_k \delta_t^k c_t^{ik} + \zeta_t + \eta_t^i, \quad i = 1, \ldots, I, \ t = 1, \ldots, T,$$

where ζ_t are time fixed effects. These are included to focus on the cross section of excess returns. Again, betas or characteristics predicting returns in sample are interpreted as explaining expected returns.

2.4 Systematic risk factors and predictive characteristics

In this section I introduce the variables that I consider as determinants of expected tranche returns. They comprise exposures to systematic risk factors on the one hand, and individual security characteristics on the other hand. I use an interest rate factor that is common in the literature, as well as returns on different portfolios of auto loan ABS tranches to capture systematic non-interest rate risk in this market. The characteristics included are ratings and WAL. In my statistical analyses in Sections 2.6 and 2.7, I test factor exposures and characteristics as alternative or competing predictors of returns.

2.4.1 Systematic risk factors

My choice of risk factors is guided by the two-factor model for corporate bonds of [39], which is the standard model in bond pricing studies. It includes an interest rate factor (commonly called TERM) and a so-called credit risk factor (DEF). I will use an interest rate factor in combination with different ways to capture non-interest rate risk using one or two auto loan ABS market factors.

Term risk

[39], like much of the subsequent literature on the cross-section of corporate bond returns (e.g. [46], [60]) use the excess return on a long-term Treasury security over the 1-month risk-free rate to capture interest rate risk. This factor measures changes in Treasury spot rates as well as in expectations about future yield curve movements. It has also been used in analyses of expected stock returns (e.g. [22]).

Interest rate factor (TERM). I define TERM to be the difference between the monthly return on a 5-year Treasury security, and the 1-month risk-free rate. The Treasury returns, as all others in this paper, are obtained from WRDS.

The regression coefficient on TERM comprehensively captures a tranche's interest rate risk.

Auto loan ABS market risk

When studying the cross section of expected returns of a particular asset class, it is commonplace to use as a systematic factor the return on a diversified portfolio of the asset class in question ([47], p. 2023). Given its broad and diversified nature, such a factor should reflect all systematic economic events relevant for prices of that asset class. If the factor uses excess returns over a corresponding-maturity Treasury return, it informs about all systematic forces relevant for security prices except yield curve effects. [39] use the return on a market portfolio of long-term corporate bonds in excess of a long-term Treasury return as factor DEF, to capture "change[s] in the likelihood of default". Auto loan ABS returns purged of interest rate effects also reflect risks that are not directly related to default, such as prepayment and liquidity risk. In this study I thus adopt the broader view that a portfolio return in excess of a corresponding Treasury return captures all non-interest rate systematic risk.

I use returns on different portfolios of auto loan ABS tranches to capture realizations of systematic risk in this market. In total, I consider four different auto loan ABS market factors.

Overall auto loan ABS market factor (AutoAll). For any given month, this factor is defined as the difference between the value-weighted average of all tranche returns with an absolute value of less than 5 percent in my sample, and the return on a Treasury security of corresponding maturity. For this and all other average tranche returns in factor formation, I require at least 11 observations in a month. Security values for weighting are calculated as the principal amount outstanding times the nominal price, both measured at the beginning of the holding period. The corresponding maturity is equal to the value-weighted average WAL of tranches in the portfolio, and for a given average WAL value the Treasury return is obtained by cubic interpolation of returns of the Treasury maturities 3 months, and 1, 2, 5, and 7 years.

The factor AutoAll is meant to capture realizations of systematic events concerning all risk categories of auto loan ABS except term structure risk. In studies of corporate bonds, e.g. [46] and [47] use the portfolio return of all (long-term) corporate bonds in their samples for analogous factor formation.

Risky auto loan ABS market factor (AutoLow). This factor too is defined as monthly excess average tranche return over a corresponding Treasury return, and is calculated analogously to AutoAll. However, for AutoLow only tranches are used that do not have a top rating at the beginning of the holding period from all agencies that rate it. A top rating means AAA from Standard&Poor's and Fitch, and Aaa from Moody's.

The reason for considering this factor as an alternative to AutoAll is that tranche risk of many non-interest rate categories is expected to be higher for lower-rated tranches. As discussed above, ratings are informative about credit risk, but also about servicer risk. Furthermore, lower-rated tranches on average have a smaller size and are older, reducing their liquidity. As a result, the systematic events that are (potentially) relevant for all tranches will produce more pronounced movements in prices of lower-rated tranches. Consequently, excess returns of only these tranches should produce a better picture of systematic risk. The corporate bond literature provides examples of the use of such a factor. [57] use only "lower-rated" bonds for calculation of their factor DEF, and [46] consider using only BBB-rated bonds for calculation of DEF.

Safe auto loan ABS market factor (AutoHigh). The calculation is again done in the same way as for AutoAll, but in this case only tranches carrying a top rating from all agencies that rated it in the previous period are used.

Despite their flawless rating, investors may price top-rated tranches differently from Treasuries due to liquidity concerns or transaction costs. Since such risks also play a role for tranches rated below AAA, the systematic factor AutoHigh is potentially relevant for prices of all tranches. The closest example in the corporate bond literature is [60], who only include investment grade bonds in the calculation of their factor DEF, even though their sample also includes junk bonds.

Differential risky auto loan ABS market factor (AutoLH). This factor aims at capturing only the risk that is specific to lower-rated tranches. AutoLow does not accomplish this, since it includes common effects in top-rated and lower-rated tranches. These effects are important, as is illustrated by the strong correlation of AutoLow with both AutoAll and AutoHigh (see Table 2.3). As a solution to this problem, I will employ a return differential between lower- and top-rated tranches. However, simply taking the difference between AutoLow and AutoHigh is not a good approach, since the average WAL of observations used for the former is generally larger. As a result, such a difference would contain a component driven by this mismatch, which would likely be related to TERM risk. I therefore find, in every month, a subsample of AAA-rated tranches whose average WAL matches that of tranches used in the calculation of AutoLow in the same month, as explained in the following.

AutoLH is defined, in every period, as the difference between the weighted-average tranche return of tranches that do not have a top rating (the same as were used for AutoLow) and a WAL-matched return of top-rated tranches. The latter is obtained as follows. In every month where the weighted average WAL of all AAA tranches is smaller than that of lower-rated ones (the target WAL in that month), I subsequently delete AAA tranches based on their WAL in steps of 0.025 years starting from the minimum of 0.25 years. After each deletion I recalculate the weighted average WAL, and I proceed until the weighted average WAL of the remaining securities falls within 1/24 year of the target WAL. I then use the weighted average return of the remaining tranches in the period as the WAL-matched return. If the value for all AAA tranches is larger than the target, I use an analogous procedure starting with elimination of the tranches with the largest WAL in a period.

The factor AutoLH measures the differential effect of systematic economic events on lower-rated tranches, and thus captures the risk that is specific to tranches rated below AAA. An approximately analogous factor for corporate bonds is used by [54] in changes of the yield spread between Baa- and Aaa-rated corporate bonds.

Factor statistics

This section presents descriptive statistics of the systematic risk factors introduced in the previous sections. Table 2.2 shows factor moments. The factor TERM has the largest average return, which is due to the longer maturity of the securities used. Average returns on the factors AutoAll, AutoLow, and AutoHigh exhibit a sensible ordering given the rating of tranches used for calculation, with more risky tranches having higher returns. Average returns on the factor AutoLH are large of similar magnitude to AutoAll, indicating that a significant share of systematic risk is only visible in lower-rated tranches. TERM, AutoAll, and AutoHigh are left-skewed, but AutoLow and AutoLH are right-skewed.

Table 2.3 shows correlations between the factors. TERM is negatively correlated to the factors AutoAll, AutoHigh, and AutoLow, which is sensible given the fact that Treasury returns enter the latter three negatively. In contrast, TERM and AutoLH have a lower correlation, which is also not statistically significant. This is in line with the stylized fact for corporate bonds that Baa-Aaa spread changes are unrelated to Treasury rate changes. Overall, all four Auto factors are rather independent of TERM, and they are less strongly correlated with TERM than [46] find their factors DEF and TERM to be, at -43 percent. Correlations between the Auto factors show a divided pattern with AutoAll and AutoHigh very strongly correlated with each other, but each very little with AutoLH. AutoLow takes a place in between, exhibiting a correlation of around 70 percent with the three others. This pattern shows that the factors capture different risks. Whereas AutoHigh, and also AutoAll (which is dominated by AAA-rated tranches), capture mostly the risk of top-rated securities, AutoLH captures only the risk of non-AAA tranches, and those risks have a low correlation with each other. AutoLow contains elements of both of these risks.

Factor models

In the remainder of the paper, I mainly consider four alternative factor model specifications. Each one includes the interest rate factor TERM. In addition, models 1, 2, and 3 have the factors AutoAll, AutoLow, and AutoLH, respectively. The first two of these proxy for overall auto loan ABS market risk. The latter specifically captures only the risk of lower-rated tranches. In order to separately account for risk captured in systematic movements of highly rated and of lower-rated tranches, model 4 includes the factor AutoHigh in addition to AutoLH. Finally, I refer to model 0 as the factor specification comprising only TERM.

Model number	Systematic factors included in the model
0	TERM
1	TERM + AutoAll
2	TERM + AutoLow
3	TERM + AutoLH
4	TERM + AutoLH + AutoHigh

2.4.2 Tranche characteristics

I include in my analysis the two characteristics most closely associated with interest rate and overall non-interest rate risk. They are a tranche's maturity, as measured by its WAL, and its credit rating. These characteristics are analogous to the ones used by [46].

Ratings

Credit ratings, which play a major role for corporate ([52], [45]) and sovereign ([21]) bond prices, are particularly important in securitized debt markets. [7] provide two reasons why that is the case. One is that the information required for tranche risk assessment, that is information about a large number of underlying borrowers, is structurally different from the information relevant for investors in corporate bonds. It may be difficult to both obtain and analyze, leading investors to rely on ratings for their investment decisions. The other reason is that asset-backed securities generally have lower credit risk and shorter maturities than corporate bonds, disincentivizing investor from conducting an own risk analysis.

Rating agencies specifically aim at gauging securities' credit risk. In terms of the risk categories listed above in section 2.2.1, their assessments are also informative about servicer risk, prepayment risk, and insurance risk, since considerations about these three categories form an integral part of their analysis. Furthermore, even though liquidity risk is explicitly *not* addressed in ratings (e.g. [66]), more highly rated securities are generally regarded as more liquid. Liquidity proxies like size or age are also positively correlated with ratings. As a result, ratings can be viewed as a comprehensive assessment covering most of securities' non-interest rate risks.

Average rating variable (Rating). My rating variables are calculated using ratings from Standard&Poor's, Moody's, and Fitch, which were by far the most important agencies in the auto loan ABS market during my sample period. From Bloomberg I get tranches' rating histories. I convert rating symbols to numerical values using the conversion AAA (Aaa for Moody's) = 15, AA+ (Aa1) = 14, AA (Aa2) = 13, and so on to B (B2) = 1, and B– (B3) = 0. The variable Rating is defined as the average numerical rating of tranche from all agencies that rated it, taken at the end of the previous month. The resulting values are then use to define dummy variables for different rating ranges.

Rating dummy variables (BtoBBB, AtoAA, AAA). I define two dummy variables based on the average rating at the end of the previous month. The variable BtoBBB is equal to 1 (and 0 otherwise) for average numerical ratings between 0 and (not including) 8.5, thus comprising ratings B– to BBB+. The variable AtoAA (equal to 1 for rating values of 8.5 to 14.99) indicates average ratings between A– and AA+. The omitted category AAA only incluldes tranches that carry a top rating of 15 from all agencies that rate it in a given period.

Weighted average life

The standard measure of maturity for securitized debt securities is the weighted average life, as explained above in section 2.3.1. It is related to the Macaulay duration, which is the weighted average time until receipt of both principal and interest payments. Prices of bonds with a longer WAL will generally move more with benchmark interest rates, and thus WAL proxies for interest rate risk.

Weighted average life (WAL). This variable is defined as a tranche's ex-post WAL at the end of the previous month.

2.5 Preliminary results

In this section, I discuss features of the time-series regressions (equation 2.2) in which betas are estimated, as well as the statistical relationships of betas and tranche characteristics. For the latter statistics, data points are tranche-month observations. Each such observation consists of the returns of a tranche in a particular month, along with betas estimated over the rolling period ending in the previous month as well as information on WAL and Rating at the end of the previous month. These tranche-month observations form the basis for portfolio sorts in section 2.6 and for the regression analyses of section 2.7. I mainly present descriptive statistics for the factor models 1 to 4 introduced in section 2.4.1. In addition, in section 2.5.1 I also report results for model 0, which consists only on the factor TERM, for comparison. Factor betas are estimated over rolling periods of 24 months length, during each of which I require a minimum of 21 return observations.

My sample yields 14316 tranche-month observations from 1120 securities. Figure 2.1 plots the total numbers of observations over time, and also separately for rating groups. Overall, the number of observations per month exhibits an increasing trend over the sample period. Observations are scarcer before 1999, with a minimum number of 36 in February and March 1997, while between February 1999 and April 2007 I have at least 98 observations in each period. The figure also shows that, while all along the majority of tranches is rated AAA, the fraction rated not AAA increased, rising from an average of 21 percent per period over the period between 12/96 and 12/01, to 35 percent between 01/04 and 04/07. However, tranches rated BBB or lower are overall rare. No such tranches are in my sample before July 1997, and while they are present in every month since, their number drops as low as 1 in February and March 2002.

Table 2.4 shows the stratification of observations regarding WAL and ratings. The majority of tranches, by far, have a top rating of AAA, but the number of observations from lower-rated tranches is also sizable. Regarding WAL, most observations fall into the shortest WAL category of 0.25 to 0.75 years, and WALs of over 2 years are rare. For longer WAL of 1.25 years or more tranches from rated below AAA are more frequent.

2.5.1 Time-series regressions results

Table 2.5 shows moments of the distributions of betas for each model, as well as average adjusted R-squareds of the time series regressions. Exposure to the factor TERM is almost universally positive and betas are mostly statistically significant in time series regressions, and the distribution is similar across models. The distributions of the auto loan ABS market factors as well exhibit a high degree of similarity. All have a positive median, but a substantial fraction of observations for each is negative. For corporate bonds, [47] also find that a (small) share of securities loads negatively on an overall market factor. At the 95th percentile, Auto betas are always highly significantly positive, except in Model 4 with its two Auto factors.

The fact that tranche returns consistently move in the same direction as Treasury returns indicates an important role of this factor. The adjusted R-squared values in Table 2.5 confirm that TERM is the most important driver of time-series variation in tranche returns, explaining over 50 percent on average. But the auto loan ABS market factors also play a role, increasing average R-squared values by up to 6.3 percentage points.

2.5.2 Correlations between factor betas and characteristics

Table 2.6 shows correlations across tranche-period observations between the different betas of each model, and between betas and tranche characteristics. I first examine the relationships between variables that are competing proxies for the same type of risk. TERM beta and tranche WAL display a strong positive relationship in all models 1 to 4, with correlations across tranche-period observations between 65 and 68 percent. Exposure to TERM and WAL seem to contain much common risk information. In their sample of corporate bonds, [46] report a somewhat lower correlation between time to maturity and TERM beta of 52 percent. Turning to non-interest rate risk, Auto factor loadings are related to ratings in the way that is expected given that factors were formed using rating information. While a higher exposure to AutoLow, and even more to AutoLH, is associated with a lower rating (correlations of -21 and -44 percent, respectively), the opposite is the case for the top-rating factor Auto-High (correlation of 10 percent with rating). Even though the overall market factor AutoAll is dominated by top-rated tranches, its beta does not exhibit overall relation to ratings. This last finding is in contrast to [46], who for corporate bonds find a correlation of -33 percent between ratings and exposure to an overall bond market factor. In summary, the information overlap between ratings and exposure to Auto factors varies across factors.

I now investigate the overall relationship between interest rate and non-interest rate risk. The correlation between ratings and WAL is -13 percent, meaning that tranches with a longer WAL on average have a lower rating. This result stands in contrast with [46], in whose corporate bond sample a longer duration is correlated with a better rating, because investors are unwilling to lend longer term to more risky companies. In my sample, lower-rated bonds are generally more subordinated, and thus have a longer WAL. With TERM beta instead of WAL as a measure of interest rate risk a similar picture of a weak positive relationship between the two risk types emerges. The correlation to ratings is negative in all models, varying between -12 and -4 percent. However, using Auto factor betas as measures of non-interest rate risk I find evidence of a mostly positive relationship between the two risk types. Exposure to the Auto factors has a correlation with WAL between 5 and 8 percent in all models. Furthermore betas for AutoAll, AutoLow, and AutoHigh exhibit positive correlations between 31 and 37 percent with TERM beta. This result is in line with the finding of [46] for corporate bonds that betas of TERM and of a market factor (DEF) are strongly positively correlated (48 percent). In their paper, they suggest measurement error in returns as explanation. An alternative view is to regard the positive correlation of [46] as a more mechanical consequence of the negative correlation of -43 percent between their factors. The same mechanism seems to be driving the results in my case. AutoAll, AutoLow, and AutoHigh all have a correlation of around -23 percent with TERM. On the other hand, betas of the factor AutoLH are uncorrelated with TERM betas, just like the correlation between the factors themselves is closer to zero and not statistically significant.

2.6 Results from portfolio sorts

I sort securities into portfolios based on their betas every month, using betas estimated over the rolling period ending in that month. Portfolio returns are then observed for the month following portfolio formation, resulting in a time series for each portfolio. Sorting is done both univariately on one beta at a time, resulting in a set of quantile portfolios for each factor in each model, as well as bivariately on two betas jointly (in model 4 I sort on TERM and AutoLH). Both univariately and bivariately I sort into nine portfolios every month. The quantile portfolios on individual factors are denoted by Q1 to Q9 in the following. To obtain bivariate sorts, I first sort on one factor into terciles (Q1 to Q3), and then divide each tercile up again three ways based on exposure to the other sorting factor. Given that my minimum number of tranche-month observations in a month is 36, sorting nine ways leaves me with at least four observations for each portfolio in every period. My main focus is on risk premia, testing whether high-beta portfolios on average generate larger returns than low-beta ones. Furthermore, I investigate how average betas and characteristics behave across sorting quantiles in order to get a better understanding of what drives average portfolio returns.

2.6.1 Univariate factor portfolio sorts

Sorts on TERM betas

First, securities are sorted on exposure to the interest rate factor TERM. The first row of each panel in Table 2.7 shows average returns for each quantile portfolio. We observe the same pattern for each model: The portfolio with the lowest TERM beta has a higher average return than the second quantile portfolio, but then returns increase monotonically with TERM beta from Q2 to Q9. Quantitatively, the results are also virtually identical across models. Panel A of Table 2.8 shows results from tests of equality of average returns between different portfolios. The difference in returns between the highest and the lowest beta portfolio is always close to 5 bps and statistically significant at the 5 percent level. I thus find evidence of a significant positive relationship between TERM betas and returns, which however breaks down at low levels of exposure. Further tests of equality reveal that the higher return of Q1 over Q2 is statistically significant, so that the pattern seems not to be caused by measurement error. In order to test if the TERM risk premium is attributable to exposure to an auto loan ABS market factor, I run regressions of returns on the portfolio that is long high-TERM beta tranches and short low-TERM beta tranches (Q9 − Q1) on the auto factors. The results in Panel B of Table 2.8 show that this portfolio has a significant alpha, confirming the risk premium for exposure to TERM.

In order to investigate which other portfolio features are related to returns, and in particular what might explain the relatively high average return on the lowest TERM quantile portfolio, Table 2.7 also shows value-weighted average betas and characteristics of the nine portfolios for each model. Overall, I find that no portfolio feature mimics the return pattern with an extremum at Q2, but ratings and AutoLH come closest. In all sorts, ratings show an inverse u-shape across quantiles, with the the peak at Q4, where the most distinctive increase in average ratings occurs between Q1 and Q2, thus matching the return drop. Portfolio WALs always show a monotonically increasing pattern (except for a slight drop between Q1 and Q2 for model 3), which is not surprising given the strong correlation between TERM betas and WAL (see Table 2.6). Finally, for the Auto factors results differ between AutoAll, AutoHigh, and AutoLow on the one hand, and AutoLH on the other. For the former three, betas increase monotonically across TERM portfolio, in line with the positive relationships between those betas and TERM beta found in Table 2.6, but do not provide any insight as to what causes the return drop from Q1 to Q2. In contrast, AutoLH betas show a distinctive drop between Q1 and Q2 in both models 3 and 4, suggesting a relation to returns. Like ratings, they form a u-shape with minimum at Q3 or Q4. In summary, the results point to ratings and AutoLH betas to play a role for returns controlling for TERM beta.

Sorts on auto loan ABS market factors

Table 2.9 shows results from univariately sorting tranches into portfolios based on betas of the Auto factors. Returns always show a u-shaped pattern across portfolios, with the minimum return occurring between Q3 and Q5. Tests of return equality between quantile portfolios are shown in Panel A of Table 2.10. I first discuss the difference between Q1 and the portfolio where the minimum return occurs for each sort (Q_{min}), and between Q9 and Q_{min}, in order to test if the u-shape is significant. For sorts on AutoAll, AutoHigh, and AutoLow, the differences between both extreme quantile Q1 and Q9 and the respective minimum return portfolio, are significantly positive, so that the general u-shape in returns in these cases is not due to measurement error. On the other hand, for AutoLH only the difference between Q9 and Q_{min} is significant, meaning that the increase in returns for low values of AutoLH beta is not statistically significant. Tests for the return difference between quantiles Q9 and Q1 reveal a similar picture, regarding risk premia. For models 1 and 2, there is no significant difference in average portfolio returns between lowest and highest betas, and neither is there for sorts on AutoHigh in model 4. In contrast, tests of return equality show a highly significant difference of 4 to 5 basis points between AutoLH beta Q9 and Q1. The finding that AutoLH is the only auto factor generating a risk premium is confirmed in Panel B of Table 2.10, which shows that the intercept in regressions of returns on a portfolio that is long high-AutoLH beta tranches and short low-AutoLH beta tranches (Q9 − Q1) on TERM (and possibly AutoHigh) is significantly positive. On the other hand, no other auto factor generates a significantly positive alpha in such a regression. Summarily, of the auto loan ABS market factors only AutoLH seems to have a univariate relationship to returns.

Looking at the behavior of average portfolio features, I find that, like returns, characteristics always have a (possibly inverted) u-shaped pattern. In the case of ratings, u-shapes qualitatively match returns regarding which portfolio attains the interior maximum. Furthermore, the levels of ratings at the extreme portfolios mimic corresponding return patterns. With respect to WAL, average portfolio values always form a u-shape, thus also generally aligning with returns. Finally, TERM betas have a u-shape that qualitatively matches returns in AutoLH sorts, while for the other Auto factors TERM beta is flat from Q1 to Q4 and then increasing. In summary, in particular ratings but also tranche WAL are related to the u-shape of returns across Auto factor portfolios, controlling for Auto beta. For TERM betas, the relationship is strongest across AutoLH-sorted portfolios.

2.6.2 Bivariate portfolio sorts

I now conduct two-way portfolio sorts in order to investigate the competing simultaneous effects of different betas on returns. In model 4 with its three factors I sort on TERM and AutoLH. Sorting is done incrementally: I first form terciles based on betas for one factor, and then subdivide each tercile group into sub-terciles based on exposure to the other factor. For each combination of sorting factors, I do both possible orders. I test return differences between high- and low-beta portfolios for each factor, and for each tercile of the other sorting factor in the respective model, resulting in six tests for each model. Panel A of Table 2.11 shows results for sorts on the factor TERM first, and results from sorts on the Auto factors first are in Panel B.

Differences in average returns between portfolios with high and low exposure to the factor TERM are always significantly positive. Risk premia fall between 3 and 5.6 bps and are roughly similar across the four models and the two sorting orders. They are always largest for medium exposure to the respective Auto factor. Average portfolio returns are in most cases monotonically increasing across TERM beta terciles, but deviations from this pattern occur from Q1 to Q2 (mostly for the highest Auto beta tercile).

For sorts on Auto betas, the results vary across factors, and the sorting order matters. The difference in returns between portfolios with high and low AutoAll exposure is never significantly non-zero, and the same is true for AutoHigh (results not reported). In contrast, sorting on beta generates positive risk premia for AutoLow and AutoLH, but the results vary across the two sorting orders. When tranches are sorted on the Auto factor first, AutoLow and AutoLH always generate risk premia that are statistically significant at the 5 percent level, yet this is not so in sorts on TERM first. In that case, in only three out of the nine tests the difference has a significance level of 5 percent, while five more have 10 percent significance, and one is not significant. The highest average significance level is obtained for AutoLH in model 4. Comparing the size of risk premia across the two sorting orders, they are lower in TERM-first sorts, and the difference is particularly pronounced in sorts where the significance level is lower in TERM-first than in Auto-first sorts. For AutoLH, risk premia average 3.7 bps in Auto-first sorts, but only 2.2 bps in TERM-first ones. Finally, regarding gradient behavior of returns across AutoLH terciles, within the highest TERM tercile they are always (weakly) monotonically increasing, whereas for the lowest they mostly exhibit a u-shape.

What drives the difference in results of sorts on Auto factors between the two sorting orders? Table 2.12 shows differences in average portfolio features between the two sorting orders, where a positive number means that the respective value is larger in Auto-first sorts. Panel B shows that Auto-first sorts generate more Auto beta variation across Auto portfolios,[11] except for the highest TERM tercile. And the same pattern is observed for ratings, where variation across Auto portfolios is larger in Auto-first sorts, but this is not the case for the highest TERM tercile. Yet in particular for the higher TERM quantile Auto beta risk premia and significance levels change much between sorting orders. A non-interest rate risk explanation through Auto betas or ratings is thus not an entirely satisfying explanantion for the difference in results between sorts. On the other hand, variation in both TERM betas as well as WAL is more pronounced precisely in those sorts where the significance level drops from one sorting order to the other. It thus seems that TERM-first sorts generate lower AutoLow and AutoLH risk premia since there is less interest rate risk variation. Overall, these observations point to a strong role for interest rate risk in auto loan ABS returns.

2.7 Regression results

I now turn to results from predictive regressions of tranche returns on factor exposures and characteristics. Section 2.7.1 presents results from classical Fama-MacBeth regressions, and section 2.7.2 discusses pooled panel regressions. For both analyses, I transform the data so that the within-period standard deviation of each factor beta is always normalized to 1. This is done to enhance comparability of cross-sectional

[11] The variation is measured by the difference in average Auto beta between Q1 and Q3. It is lower in Auto-first sorts for Auto-Q1 (negative number in the table), and higher for Auto-Q3. Thus the difference is larger in Auto-first sorts.

regression results over time for Fama-MacBeth average coefficients, and of observations across periods for the panel regressions. Without the normalization, within-period standard deviations of factor betas vary substantially over time. The normalization allows me to strengthen my focus on the cross section of returns.

2.7.1 Fama-MacBeth regressions

In Table 2.13 I report, for each specification of the predictive period-by-period cross-sectional equation 2.3, Fama-MacBeth coefficient averages over time, together with corresponding standard errors. Furthermore, the table shows time series averages of cross-sectional adjusted R-squareds. I first discuss results of the models including only factor betas as return predictors, and then investigate how factor roles change when characteristics are included as additional variables. Again, I study factor models 1 to 4 introduced in section 2.4.1.

Factor models without characteristics

Average cross-sectional coefficients of TERM beta are found to always be statistically different from zero, even though in model 3 only at the 10 percent level. The point estimates vary between 1.3 and 1.9. The interpretation of these numbers is that a tranche whose exposure to TERM is one standard deviations higher in a given period is predicted to have a return in the next period that is 1.3 to 1.9 bps larger. In other words, the factor TERM is priced in the cross section of auto loan ABS returns. This result is in line with the earlier finding that portfolios of tranches with a greater exposure to TERM earn signicantly higher average returns.

Across the auto loan ABS market factors, results vary regarding their role for tranche pricing. On the one hand, average cross-sectional slope coefficients of exposure to the factors AutoAll and AutoHigh are not statistically different from zero. On the other hand, AutoLow and AutoLH display strong pricing ability, with average cross-sectional coefficients of both factors very significantly positive. The average coefficients on AutoLH (1.6 and 1.9) are somewhat larger than the one on AutoLow (1.3), meaning that variation in exposure to the former is associated with larger return differentials. Larger risk premia of AutoLH than of AutoLow had also been found in univariate and bivariate portfolio sorts above. The results support the view that lower-rated tranches convey a better picture of relevant systematic risk events.

Controlling for characteristics

I now include rating group dummies and tranche WAL as additional variables into the cross-sectional regressions in order to investigate robustness of the factor pricing results in the previous section. The characteristics are added individually as well as jointly. The average coefficients on AutoAll and AutoHigh betas are never significant when controlling for any combination of characteristics, and thus I will not discuss them further.

Controlling for tranche WAL has effects on the predictive capabilities of some betas. In no model, the average coefficient on TERM beta is significantly positive when WAL is included, meaning that exposure to TERM does not carry a positive risk premium. In model 3, the average slope of TERM beta is actually negative at the 10 percent level. The interpretation of this is that to describe the relationship between interest rate risk and expected returns both variables are needed, and TERM beta does contain information about tranche risk above and beyond what is contained in WAL. In contrast, the factors AutoLow and AutoLH both show up very significantly positive in the presence of WAL as control variable, indicating that the risk measured by exposure to them is priced independent of WAL. The average coefficients are actually always larger compared to the case without WAL.

The inclusion of ratings has no effect on the pricing results for TERM, leaving estimates and significance levels largely unchanged. This result is sensible, since exposure to TERM measures interest rate risk, which is not accounted for in ratings. In contrast, the predictive power of betas of the factors AutoLow and AutoLH is reduced in the presence of ratings. In models 2 and 4 the average coefficient is not distinguishable from zero, while in model 3 it stays significant at the 5 percent level, but the coefficient size is much smaller than before, at 0.8 bps. It thus seems that in regressions with ratings but without WAL, ratings take over much of the role of Auto betas.

However, this is not so when I include both WAL and rating dummies in second-stage Fama-MacBeth regressions. Compared to the previous case of ratings only, Auto betas regain much of their significance and are always significant at the 5 percent level, even if average coefficients are always smaller than in the case with characteristics. This result confirms the role of exposure to AutoLow and AutoLH for pricing found above in portfolio sorts. Their betas contain information about priced tranche risks beyond what is contained in ratings. However, detecting this in the data requires controlling for the relationship between WAL and next-period return.

The results in the last panel of table 2.13, of Fama-MacBeth regressions on characteristics only, show that rating dummies and WAL are always extremely statistically significant. In fact this is also the case when they are combined with any combination of factors. It seems thus that characteristics overall are more important for returns than factor exposures. However, even though the average adjusted R^2 generated by characteristics alone is larger than that of any factor model, it is always raised substantially by adding factors. This underlines the above result that at least AutoLH and AutoLow play an autonomous role for expected returns.

2.7.2 Panel regressions

In my final tests I run panel regressions using all tranche-month observations. For each of the factor combinations of models 0 to 4, I test four specifications like previously in Fama-MacBeth regressions: Without characteristics and with rating and WAL individually and jointly. I also run regressions only on characteristics without betas. All regressions include month fixed effects,[12] and I use standard errors clustered at the monthly level to allow for non-independent errors and/or heteroskedasticity within a period. I do not include security fixed effects, since that is precisely the variation I want to pick up with my covariates. The question is not whether betas and characteristics predict a high security return relative to the average return of that particular security, but whether they predict a high return for a security in a period relative to other securities. As before the within-period cross-sectional standard deviation of each beta is normalized to one. As a consequence, the coefficient estimates capture only effects of within-period variation of pre-determined betas on the cross section of next-period returns. In other words, they do not capture a possible relationship between exposure *levels* and subsequent returns. Only for WAL and ratings coefficients capture a relation between absolute levels of the characteristics and relative next-period returns.

The panel regressions in Table 2.14 confirm previous pricing results for the Auto factors. The coefficients on betas of AutoLow and AutoLH are positive and significant in all specifications, and thus are determinants of expected returns as had been found in univariate portfolio sorts and in Fama-MacBeth regressions. Again coefficient mag-

[12] Following [20] (p. 831) I use time fixed effects instead of random effects, since time dummy coefficients are correlated with average monthly regressors. I test this by estimating monthly dummy coefficients for each model and each characteristics combination, and the regress the estimates on monthly averages of betas and chars. Betas and chars show up significantly.

nitudes depend on the inclusion of ratings as control variables, which diminishes them by about half (from around 2 to around 1 basis point) like before. The coefficients are slightly larger, but of similar magnitude to Fama-MacBeth regressions. In model 4, e.g. a difference of one within-period standard deviation of AutoLH beta predicts the next-period return to be 1 basis point higher. On the other hand, AutoAll and AutoHigh are never significantly priced, as had been found in all previous tests.

The results in Table 2.14, on the other hand, do not provide evidence in favor of an effect of exposure to the interest rate factor TERM on expected returns. While the coefficients exhibit the same pattern regarding their signs as in Fama-MacBeth regressions, that is, positive when not controlling for WAL and otherwise negative, they are hardly significant. In particular, in regressions without controlling for characteristics, which was the case that produced the most positive pricing evidence of TERM before, the coefficient is only significant for models 0 and 1, and only at the 10-percent level. The negative coefficient found for TERM beta when controlling for WAL is only significant once, at the 5-percent level. I conclude that panel regressions do not provide evidence that the interest rate factor is significantly priced in returns one way or the other.

A large part of the adjusted R^2 in panel regression is achieved through month fixed effects only. However, adding factors to any specification increase increases adjusted R^2. Ratings and WAL are significantly priced in all specifications, and in a sensible way with the coefficient on BtoBBB always larger than the one on AtoAA, which is in turn always positive. Inclusion of TERM beta raises the coefficient on WAL, in line with the negative coefficient on the former observed in these cases. Inclusion of AutoLow and AutoLH always reduces rating dummy coefficient estimates.

2.8 Conclusions

In this paper, I have studied the cross section of expected auto loan ABS returns, using portfolio sorting and regression techniques. Sorting allows me to study the effects of one or two factor betas at a time, and results indicate the existence of factor risk premia for exposure to TERM and AutoLH, and also to some extent for AutoLow. Fama-MacBeth and panel regressions then enable me to study the effects of betas and characteristics at the same time. A principal result is confirmation of the role of exposure to AutoLH for pricing. The coefficient is significant in all but one specification, including when controlling for the effects of ratings and WAL. In addition, AutoLow displays a similarly strong role in regressions. On the other hand, the evidence regarding TERM becomes mixed. In Fama-MacBeth regressions it is only priced when WAL is not included as a control variable. And in panels the point estimate is positive without characteristics or controlling for ratings, but coefficients on TERM are overall not distinguishable from zero. However, interest rate risk does seem to be important for pricing, as evidenced by highly significant coefficients on WAL in all regressions.

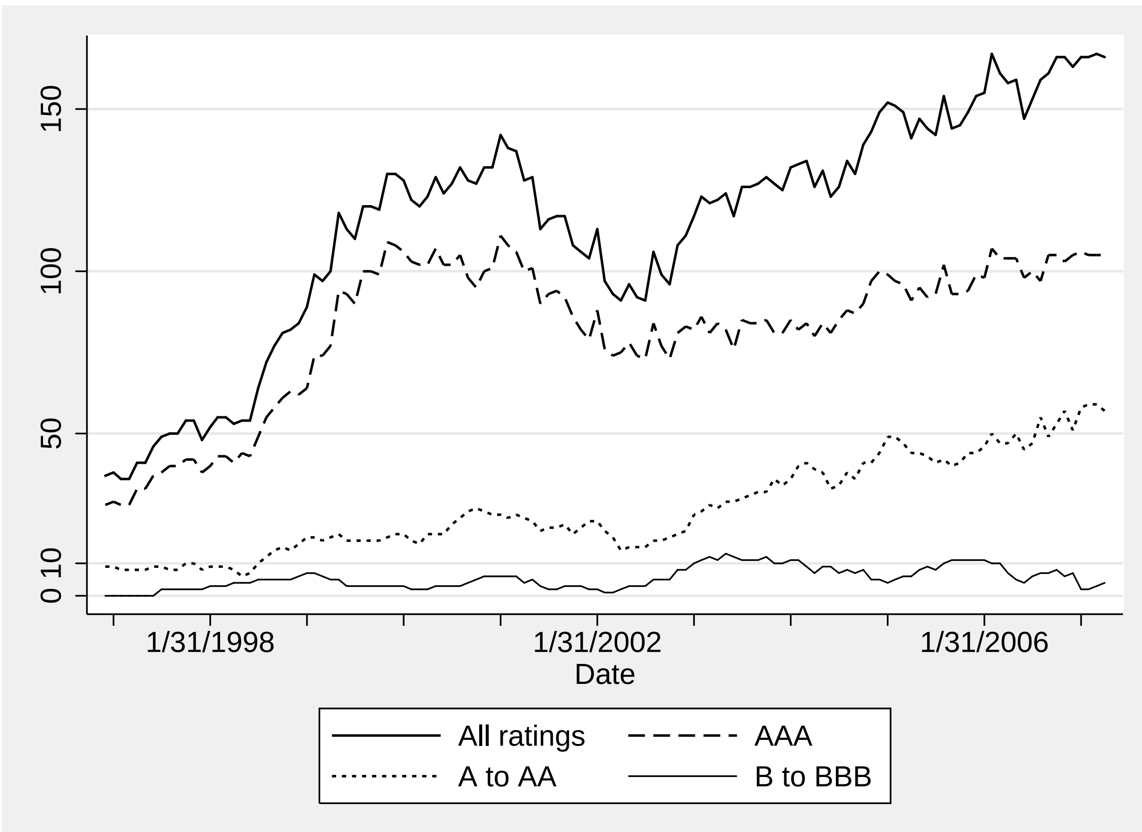

Figure 2.1: Number of observations per period. The graph shows the number of tranche-months observations per month, both overall and separately by rating groups. A tranche-month observation is a tranche in a month where it has a return observation and in addition betas estimated over the 24-month rolling period ending in the previous month as well as information on WAL and Rating at the end of the previous month. There are no observations from tranches rated below A- before July 1997, and only one in February and March 2002.

Table 2.1: Distributions of excess returns over the 1-month risk-free rate. The table contains descriptive statistics of my sample of monthly tranche excess return over the 1-month risk-free rate (measured as the 30-day T-bill return). I exclude observations that lack information on rating and WAL at the beginning of the month, as well as with a WAL of less than a quarter year. Furthermore, I exclude tranches that have fewer than 22 observations, since in this case they cannot be used for my later analysis. The statistics in the table are calculated from returns of 1299 tranches. Panel A includes all remaining observations, whereas for Panel B excess returns that are smaller than -5 percent, or larger than 5 percent, are excluded. This is tantamount to cutting the distribution at percentiles 0.042 and 99.937, which eliminates 47 observations, all of which are from tranches rated lower than AAA in the month. I report statistics for all observations, as well as separately by classes formed on ratings. In Panel B I do not report the distribution of AAA-rated classes, since no observations from this class are eliminated when cutting the distribution.

	Mean	Stardard deviation	Minimum	Median	Max-imum	Number of observa-tions
Panel A.						
All ratings	.137	.623	-29.14	.085	39.524	45,378
AAA	.121	.404	-3.419	.079	4.094	33,285
BtoAA	.182	1.002	-29.14	.103	39.524	12,093
Panel B.						
All ratings	.135	.453	-4.985	.085	4.918	45,331
BtoAA	.174	.565	-4.985	.103	4.918	12,046

Table 2.2: Descriptive statistics of the risk factors. The table contains descriptive statistics of the five systematic risk factors introduced in Section 2.4.1. For each, there are 149 monthly observations covering the period December 1994 to April 2007. All factor means are statistically different from zero at the 5-percent level.

	Mean	Stan-dard Deviation	Min-imum	10th Percentile	Median	90th Percentile	Max-imum
TERM	0.207	1.223	-3.460	-1.456	0.231	1.855	3.259
AutoAll	0.035	0.106	-0.335	-0.095	0.046	0.165	0.291
AutoHigh	0.033	0.106	-0.357	-0.102	0.039	0.165	0.299
AutoLow	0.082	0.188	-0.696	-0.100	0.080	0.304	0.744
AutoLH	0.044	0.140	-0.642	-0.061	0.041	0.178	0.737

Table 2.3: Factor correlations. The table shows correlations between the risk factors. Each correlation is calculated using 149 monthly observations covering the period December 1994 to April 2007. One, two, and three stars indicate that a correlation is statistically different from zero at the significance level 10, 5, or 1 percent, respectively.

	TERM	AutoAll	AutoHigh	AutoLow	AutoLH
TERM	1				
AutoAll	-0.241***	1			
AutoHigh	-0.223***	0.992***	1		
AutoLow	-0.231***	0.699***	0.641***	1	
AutoLH	0.119	0.128	0.0590	0.704***	1

Table 2.4: Numbers of tranche-month observations by WAL and ratings. The table shows the stratification of tranche-month observations by weighted average life and average rating. A tranche-month observation is a tranche in a month where it has a return observation and in addition betas estimated over the 24-month rolling period ending in the previous month as well as information on WAL and Rating at the end of the previous month. Numerical rating values are average ratings as explained in the text. Rating symbols refer to the ones used by S&P's and Fitch on the one hand, and Moody's on the other hand. The table includes observations from 1120 tranches.

Rating symbol			WAL in years		
(Numerical range)	0.25 to 0.75	0.75 to 1.25	1.25 to 2	More than 2	Total
B/B (0-2.5)	12	12	9	4	37
BB/Ba (2.5-5.5)	28	30	15	4	77
BBB/Baa (5.5-8.5)	288	191	70	14	563
A/A (8.5-11.5)	803	642	348	50	1,843
AA/Aa (11.5-14.99)	911	560	54	1	1,526
AAA/Aaa (14.99-15)	5,933	3,276	917	144	10,270
Total	7,975	4,711	1,413	217	14,316

Table 2.5: Distributions of estimated betas and time-series t-statistics, and average R-squareds. The table characterizes the distribution of estimated betas for each risk factor in each model 0 to 4, as well as the distributions of t-statistics from the time series regressions where the betas are estimated. In each model, the statistics refer to the distributions of betas and t-values across 14316 tranche-month observations. In particular, a given t-statistic does not necessarily refer to the beta next to it. In addition the table shows, for each model, the average value of adjusted R-squared obtained in the rolling time series regressions where betas are estimated.

	Model 0		Model 1				Model 2			
	TERM		TERM		AutoAll		TERM		AutoLow	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
5th %tile	.055	1.519	.061	1.627	-1.252	-2.225	.054	1.47	-.848	-1.885
Median	.189	5.333	.207	5.401	.415	.939	.193	5.36	.234	1.028
95th %tile	.459	10.923	.496	10.889	1.89	3.434	.492	11.136	1.174	4.212
Avg. adj. R^2	.511		.552				.559			

	Model 3				Model 4					
	TERM		AutoLH		TERM		AutoHigh		AutoLH	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
5th %tile	.049	1.408	-.88	-1.531	.058	1.536	-1.251	-2.194	-.964	-1.721
Median	.185	5.137	.21	.583	.204	5.12	.374	.852	.137	.394
95th %tile	.451	10.916	1.703	3.436	.478	10.733	1.762	3.25	1.604	3.306
Avg. adj. R^2	.542				.574					

Table 2.6: Correlation between betas, and between betas and characteristics. The table shows, for models 1 to 4, correlations between betas as well as between betas and characteristics. Furthermore, it contains the correlation between WAL and average rating, which is model-independent, in the last column. All correlations are calculated across 14316 tranche-month observations. A tranche-month observation is a tranche in a month where it has a return observation and in addition betas estimated over the 24-month rolling period ending in the previous month as well as information on WAL and Rating at the end of the previous month.

	Model 1		Model 2		Model 3		Model 4			
	TERM	Auto-All	TERM	Auto-Low	TERM	Auto-LH	TERM	Auto-High	Auto-LH	WAL
AutoAll	.369	1	.	.	.	.	.	.	.	.
AutoLow	.	.	.376	1	.	.	.	.	.	.
AutoLH	.	.	.	.	.047	1	-.011	-.143	1	.
AutoHigh	.	.	.	.	.	.	.312	1	-.143	.
Rating	-.079	-.005	-.116	-.21	-.063	-.439	-.036	.102	-.442	-.127
Wal	.662	.078	.647	.083	.658	.072	.675	.06	.049	.

Table 2.7: Portfolio sorts on TERM betas. Tranches are sorted on TERM beta into 9 quantile portfolios each month as explained in the text. This is done for each model over the period 12/96 to 04/07. In each month for each quantile portfolio, value-weighted averages of excess return over the risk-free rate, TERM beta, Auto betas in the respective model, rating, and WAL are calculated using the tranche in the portfolio in the month. Value weighting is done on tranche size, defined as the nominal price times the outstanding principal balance, both at the beginning of the month. The table reports time series averages of the previous 5 portfolio features, for models 1 to 4 and for the nine quantiles Q1 to Q9. The median number of tranches in a portfolio in a month is 13.67, and the minimum is 4. Returns are in percent per month. Ratings are in the numerical scale introduced in section 2.4.2. WAL is in years.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
Model 1 (TERM + AutoAll).									
Return	.079	.056	.06	.067	.071	.077	.089	.111	.129
TERM	.07	.12	.14	.17	.21	.25	.3	.36	.47
AutoAll	.12	.21	.22	.28	.34	.38	.38	.45	.71
Rating	14.14	14.6	14.76	14.78	14.71	14.68	14.63	14.4	13.72
WAL	.47	.47	.51	.55	.61	.71	.87	1.07	1.44
Model 2 (TERM + AutoLow).									
Return	.08	.056	.061	.062	.068	.077	.095	.112	.13
TERM	.06	.11	.13	.16	.2	.24	.29	.35	.46
AutoLow	.09	.11	.12	.14	.17	.19	.2	.29	.51
Rating	14.25	14.65	14.8	14.82	14.73	14.7	14.65	14.35	13.48
WAL	.47	.47	.5	.55	.61	.73	.88	1.08	1.43
Model 3 (TERM + AutoLH).									
Return	.082	.056	.058	.064	.068	.075	.09	.111	.129
TERM	.05	.1	.12	.15	.19	.22	.27	.33	.43
AutoLH	.33	.16	.06	.09	.1	.14	.17	.21	.31
Rating	14.13	14.55	14.75	14.76	14.69	14.69	14.61	14.43	13.88
WAL	.47	.45	.49	.55	.61	.7	.87	1.05	1.45
Model 4 (TERM + AutoLH + AutoHigh).									
Return	.078	.058	.058	.063	.07	.073	.091	.112	.13
TERM	.06	.11	.14	.17	.21	.25	.29	.35	.46
AutoHigh	.09	.25	.25	.27	.3	.36	.34	.44	.59
AutoLH	.24	.04	.03	0	.01	.05	.09	.07	.17
Rating	14.1	14.58	14.72	14.76	14.7	14.66	14.59	14.46	13.92
WAL	.46	.47	.5	.53	.62	.7	.87	1.05	1.45

Table 2.8: TERM risk premia. Panel A shows results from tests of equality between average returns of quantile portfolios formed on TERM betas. For each model 1 to 4, I test differences between the ninth and the first quantile, and between the first and the second. I report the mean return difference in percent, as well as standard errors in parentheses. E.g. the value of .05 for Q9-Q1 for Model 1 in the top-left cell is the difference between .129 and .079 in the last and the first cells in the top row of Table 2.7. For Panel B I run time-series regressions of the return difference between the ninth and the first TERM beta quantile portfolios, where the covariates consists of the respective Auto factor(s) in each model. The table shows estimates of regression intercepts obtained with OLS. One, two, and three stars indicate that a return difference or a regression intercept is statistically different from zero at the significance level 10, 5, or 1 percent, respectively.

	Model 1	Model 2	Model 3	Model 4
Panel A. Return differences.				
Q9 - Q1	.05**	.051**	.047**	.053**
	(.025)	(.022)	(.031)	(.014)
Q1 - Q2	.023***	.024***	.026***	.02***
	(.004)	(.002)	(0)	(.004)
Panel B. Portfolio alphas.				
Q9 - Q1	.075***	.075***	.042*	.066***
	(.001)	(.002)	(.069)	(.004)

Table 2.9: Portfolio sorts on Auto factor betas. Tranches are sorted on Auto betas into 9 quantile portfolios each month as explained in the text. This is done for each model for each Auto factor over the period 12/96 to 04/07. In each month for each quantile portfolio, value-weighted averages of excess return over the risk-free rate, TERM beta, Auto betas in the respective model, rating, and WAL are calculated using the tranche in the portfolio in the month. Value weighting is done on tranche size, defined as the nominal price times the outstanding principal balance, both at the beginning of the month. The table reports time series averages of the previous 5 portfolio features, for models 1 to 4 and for the nine quantiles Q1 to Q9. In models 1 to 3 I sort on the single Auto factor included, and in model 4 I sort on both Auto factors individually. The median number of tranches in a portfolio in a month is 13.67, and the minimum is 4. Returns are in percent per month. Ratings are in the numerical scale introduced in section 2.4.2. WAL is in years.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9
Model 1. Sorts on AutoAll.									
Return	.096	.085	.074	.075	.081	.077	.078	.082	.107
TERM	.22	.22	.22	.22	.23	.25	.27	.29	.34
AutoAll	-.45	-.06	.08	.2	.32	.43	.58	.8	1.45
Rating	14.19	14.63	14.68	14.72	14.73	14.73	14.66	14.44	13.73
WAL	.82	.74	.71	.7	.72	.73	.78	.87	1.01
Model 2. Sorts on AutoLow.									
Return	.089	.077	.08	.067	.073	.083	.091	.103	.112
TERM	.21	.2	.21	.21	.23	.24	.27	.3	.35
AutoLow	-.25	-.03	.05	.11	.18	.25	.36	.52	1.16
Rating	14.65	14.81	14.83	14.86	14.84	14.75	14.54	13.93	12.22
WAL	.82	.69	.72	.68	.73	.77	.88	.92	1.01
Model 3. Sorts on AutoLH.									
Return	.083	.071	.067	.072	.078	.086	.094	.102	.126
TERM	.25	.22	.21	.22	.22	.23	.24	.26	.28
AutoLH	-.51	-.21	-.08	.03	.14	.26	.42	.68	2
Rating	14.89	14.93	14.93	14.93	14.87	14.76	14.35	13.58	11.12
WAL	.87	.72	.69	.71	.76	.8	.87	.88	.94
Model 4.									
Sorts on AutoHigh.									
Return	.098	.085	.081	.077	.075	.075	.076	.08	.106
TERM	.22	.22	.22	.22	.23	.23	.25	.28	.32
AutoHigh	-.51	-.09	.05	.18	.3	.42	.54	.73	1.26
AutoLH	.41	.11	.05	.02	-.01	-.04	0	.02	.28
Rating	13.86	14.36	14.49	14.69	14.71	14.77	14.69	14.65	14.23
WAL	.81	.76	.72	.7	.71	.71	.76	.84	1.01
Sorts on AutoLH.									
Return	.08	.07	.074	.07	.077	.086	.1	.097	.127
TERM	.28	.24	.24	.24	.24	.25	.27	.27	.3
AutoHigh	.49	.39	.38	.33	.29	.3	.31	.31	.33
AutoLH	-.6	-.3	-.16	-.05	.06	.18	.34	.59	1.91
Rating	14.88	14.94	14.95	14.94	14.86	14.75	14.3	13.64	10.97
WAL	.88	.73	.72	.72	.74	.8	.85	.85	.94

Table 2.10: Auto factor risk premia. Panel A shows results from tests of equality between average returns of quantile portfolios formed on Auto betas. For each model 1 to 4 for each Auto factor, I test differences between three quantile combinations. In each case I compare the ninth and the first quantile. Furthermore, in each sort I compare both the first and the ninth quantile to the quantile with the minimum average return, denoted in the table as Q_{min}. Specifically, Q_{min} is Q3 in Model 1, Q4 in Model 2, Q3 in Model 3, and Q5 and Q4 in Model 4 for AutoHigh and AutoLH, respectively. In each case, I report the mean return difference in percent, as well as standard errors in parentheses. E.g. the value of .01 for Q9-Q1 for Model 1 in the top-left cell is the difference between .107 and .097 in the last and the first cells in the top row of Table 2.9. For Panel B I run time-series regressions of the return difference between the ninth and the first Auto beta quantile portfolios, for each model and each Auto factor. The covariates consist of TERM only in models 1 to 3, and TERM and the respective other Auto factor in model 4. The table shows estimates of regression intercepts obtained with OLS. One, two, and three stars indicate that a return difference or a regression intercept is statistically different from zero at the significance level 10, 5, or 1 percent, respectively.

	Model 1	Model 2	Model 3	Model 4	
Sort on:	AutoAll	Auto-Low	AutoLH	Auto-High	AutoLH
Panel A. Return differences.					
Q9 - Q1	.01	.023	.043***	.008	.047***
	(.407)	(.228)	(.003)	(.477)	(.001)
Q1 - Q_{min}	.022***	.023***	.016**	.023***	.01
	(.002)	(.003)	(.038)	(.007)	(.198)
Q9 - Q_{min}	.032***	.045**	.059***	.031***	.057***
	(.006)	(.014)	(0)	(.002)	(0)
Panel B. Portfolio alphas.					
Q9 - Q1	.007	.02	.041***	$-.005$	.036**
	(.55)	(.298)	(.005)	(.677)	(.015)

Table 2.11: Average portfolio returns, and return differences, in bivariate portfolio sorts. Tranches are sorted into terciles on both TERM and Auto betas each month, resulting in 3-by-3 portfolios as explained in the text. This is done for each model over the period 12/96 to 04/07, where for Model 4 I sort on TERM and AutoLH, but not on AutoHigh. In Panel A, sorting is done on TERM betas first, and then each resulting tercile is again sorted three-ways on Auto betas. In Panel B, the sorting order is reversed. In each month for each portfolio, value-weighted averages of excess return over the risk-free rate are calculated using the portfolio tranches in that month. Value weighting is done on tranche size, defined as the nominal price times the outstanding principal balance, at the beginning of the month. Each panel reports time series averages of excess returns, for models 1 to 4 and for each of the 3-by-3 portfolios. The median number of tranches in a portfolio in a month is 13.67, and the minimum is 4. Furthermore, each panel contains results from tests of equality between average returns. For each model, I test 6 return differences. Namely, for each TERM beta tercile I test the difference between Auto-Q3 and Auto-Q1 (reported below the 3-by-3 average returns), and for each Auto tercile I test the difference between TERM-Q3 and TERM-Q1 (reported to the right of the 3-by-3 average returns). In each case, I report the mean return difference in percent, as well as standard errors in parentheses. One, two, and three stars indicate that a return difference is statistically different from zero at the significance level 10, 5, or 1 percent, respectively. Returns are in percent per month.

Panel A. TERM-first sorts.

Model 1 (TERM + AutoAll).						
Sorts on:			TERM		Return difference	
		Q1	Q2	Q3	Q3 - Q1	
	Q1	.066	.074	.109	.043***	(.001)
AutoAll	Q2	.053	.073	.1	.048***	(0)
	Q3	.073	.071	.119	.047***	(.006)
Return difference	Q3-Q1	.007	-.003	.011		
		(.341)	(.689)	(.296)		
Model 2 (TERM + AutoLow).						
	Q1	.069	.069	.107	.038***	(.001)
AutoLow	Q2	.051	.067	.106	.055***	(0)
	Q3	.084	.08	.125	.041**	(.015)
Return difference	Q3-Q1	.015*	.011	.018*		
		(.081)	(.115)	(.067)		
Model 3 (TERM + AutoLH).						
	Q1	.058	.068	.104	.047***	(.001)
AutoLH	Q2	.054	.065	.107	.053***	(0)
	Q3	.091	.08	.122	.031**	(.04)
Return difference	Q3-Q1	.033***	.012*	.018*		
		(0)	(.06)	(.068)		
Model 4 (TERM + AutoLH + AutoHigh).						
	Q1	.058	.067	.105	.047***	(.001)
AutoLH	Q2	.053	.064	.108	.056***	(0)
	Q3	.091	.084	.121	.03**	(.046)
Return difference	Q3-Q1	.033***	.017**	.016*		
		(0)	(.019)	(.087)		

Panel B. Auto-first sorts.

Model 1 (TERM + AutoAll).						
Sorts on:			TERM		Return difference	
		Q1	Q2	Q3	Q3 - Q1	
	Q1	.074	.07	.108	.034***	(.003)
AutoAll	Q2	.055	.07	.097	.042***	(0)
	Q3	.074	.078	.11	.036**	(.03)
Return difference	Q3-Q1	0	.008	.002		
		(.993)	(.427)	(.897)		
Model 2 (TERM + AutoLow).						
	Q1	.067	.064	.1	.032***	(.007)
AutoLow	Q2	.052	.065	.101	.049***	(0)
	Q3	.089	.088	.133	.044**	(.015)
Return difference	Q3-Q1	.021**	.024**	.033**		
		(.023)	(.011)	(.02)		
Model 3 (TERM + AutoLH).						
	Q1	.058	.06	.094	.036***	(.003)
AutoLH	Q2	.055	.066	.104	.05***	(0)
	Q3	.094	.095	.128	.034**	(.031)
Return difference	Q3-Q1	.037***	.035***	.034***		
		(0)	(0)	(.007)		
Model 4 (TERM + AutoLH + AutoHigh).						
	Q1	.058	.06	.092	.034***	(.005)
AutoLH	Q2	.053	.067	.1	.047***	(0)
	Q3	.099	.096	.131	.033**	(.044)
Return difference	Q3-Q1	.041***	.037***	.04***		
		(0)	(0)	(.001)		

Table 2.12: Differences in average portfolio features between sorting orders of bivariate portfolios. Tranches are sorted into terciles on both TERM and Auto betas each month, resulting in 3-by-3 portfolios as explained in the text. For each model, I obtain two sets of 3-by-3 portfolios for the two sorting orders (TERM beta or Auto beta first). For each each sorting order and each TERM-Auto beta tercile combination, I calculate value-weighted averages of TERM beta, Auto beta (AutoLH in Model 4), rating, and WAL in each month. Value weighting is done on tranche size, defined as the nominal price times the outstanding principal balance, at the beginning of the month. I then calculate time series averages of the previous 4 portfolio features for each sorting order and each 3-by3 portfolio. The table reports differences of those time series averages between the two sorting orders. Panel A contains, for each model and each 3-by-3 portfolio, the difference in average TERM beta between Auto beta-first sorting and TERM beta-first sorting. Similarly, Panels B, C, and D, contain differences in average Auto beta, average rating, and average WAL, respectively. E.g. the positive value of .01 in the upper left cell of Panel C means that, in Model 1, the portfolio with the lowest TERM beta and the lowest Auto beta has a higher rating when sorting is done on Auto beta first, in comparison to when sorting is done on TERM beta first. Ratings are in the numerical scale introduced in section 2.4.2. WAL is in years.

Panel A. TERM beta differences.				
Model 1.				
Sorts on:		TERM		
		Q1	Q2	Q3
	Q1	.01	-.02	-.05
AutoAll	Q2	.02	-.01	-.04
	Q3	.05	.05	0
Model 2.				
	Q1	0	-.03	-.05
AutoLow	Q2	.01	-.01	-.03
	Q3	.05	.06	.02
Model 3.				
	Q1	.01	0	-.02
AutoLH	Q2	.01	-.01	-.02
	Q3	.01	.03	.01
Model 4.				
	Q1	.02	.01	-.01
AutoLH	Q2	0	-.01	-.03
	Q3	.01	.02	.01

Panel B. Auto beta differences.				
Model 1.				
Sorts on:		TERM		
		Q1	Q2	Q3
	Q1	-.05	-.09	-.19
AutoAll	Q2	.08	.01	-.14
	Q3	.23	.07	-.01
Model 2.				
	Q1	-.01	-.01	-.12
AutoLow	Q2	.05	.01	-.12
	Q3	.17	.09	-.13
Model 3.				
	Q1	-.04	-.01	-.08
AutoLH	Q2	0	.04	-.08
	Q3	.1	.19	-.23
Model 4.				
	Q1	-.05	-.04	-.06
AutoLH	Q2	-.02	.03	-.04
	Q3	.04	.2	-.2

Panel C. Rating differences.				
Model 1.				
Sorts on:		TERM		
		Q1	Q2	Q3
	Q1	-.11	-.14	.01
AutoAll	Q2	.14	.02	.05
	Q3	-.18	.04	.02
Model 2.				
	Q1	-.09	-.08	0
AutoLow	Q2	.07	0	.24
	Q3	-.23	-.17	.34
Model 3.				
	Q1	.04	0	-.03
AutoLH	Q2	.1	0	.24
	Q3	-.2	-.45	.39
Model 4.				
	Q1	.02	0	-.01
AutoLH	Q2	.15	-.01	.21
	Q3	-.14	-.43	.24

Panel D. Wal differences.				
Model 1.				
Sorts on:		TERM		
		Q1	Q2	Q3
	Q1	.01	-.01	-.08
AutoAll	Q2	.01	-.03	-.09
	Q3	.06	.17	.02
Model 2.				
	Q1	-.01	-.07	-.11
AutoLow	Q2	-.03	-.01	-.09
	Q3	.08	.16	.11
Model 3.				
	Q1	0	.01	-.04
AutoLH	Q2	-.01	-.02	-.08
	Q3	.02	.09	.11
Model 4.				
	Q1	.01	.03	-.04
AutoLH	Q2	-.01	-.02	-.08
	Q3	.01	.09	.08

Table 2.13: Fama-MacBeth regression results. In each month, I run cross-sectional regressions of returns on betas estimated over the rolling period ending in the previous month, and on tranche characteristics at the beginning of the month. The table contains time series averages of cross-sectional parameter estimates ("Fama-MacBeth average slope coefficients"), along with results from t-tests of the average being equal to zero. A row of coefficients corresponds to a cross-sectional specification, with standard errors underneath in parentheses. One, two, and three stars indicate significance levels of 10, 5, and 1 percent, respectively. I run period-by-period cross-sectional regressions including various covariate combinations of betas and characteristics. In Panel A, each factor model 1 to 4 is tested without characteristics. In Panels B to E, each model 1 to 4 is tested with rating dummies and WAL as controls (individually and jointly). Finally, Panel F contains results from regressions only on characteristics. Each cross-sectional regression includes a constant term, whose average coefficient is not reported. I also document in the last column, for each specification, the time series average of cross-sectional adjusted R-squared. Figure 2.1 informs about the number of observations per period.

TERM	AutoAll	Auto-Low	AutoLH	Auto-High	BtoBBB	AtoAA	WAL	Avg. adj. R^2
Models 1 to 4, no characteristics.								
1.90**	0.060	.	.	.	.	.	.	0.22
(0.80)	(0.43)	.	.	.	.	.	.	.
1.94**	.	1.3**	.	.	.	.	.	0.25
(0.81)	.	(0.46)	.	.	.	.	.	.
1.33*	.	.	1.94***	.	.	.	.	0.25
(0.70)	.	.	(0.38)	.	.	.	.	.
1.84**	.	.	1.59***	-0.33	.	.	.	0.27
(0.80)	.	.	(0.40)	(0.44)	.	.	.	.
Model 1.								
1.76**	-0.060	.	.	.	11.7***	1.80***	.	0.29
(0.78)	(0.38)	.	.	.	(1.87)	(0.51)	.	.
-0.32	0.47	.	.	.	.	.	7.14***	0.30
(0.58)	(0.34)	.	.	.	.	.	(1.80)	.
-0.63	0.36	.	.	.	12.2***	2.25***	7.05***	0.37
(0.57)	(0.31)	.	.	.	(1.79)	(0.52)	(1.80)	.

TERM	AutoAll	Auto-Low	AutoLH	Auto-High	BtoBBB	AtoAA	WAL	Avg. adj. R^2
Model 2.								
1.91**	.	0.30	.	.	10.7***	1.52***	.	0.29
(0.82)	.	(0.44)	.	.	(1.85)	(0.51)	.	.
-0.55	.	1.96***	.	.	.	.	7.16***	0.32
(0.59)	.	(0.38)	.	.	.	.	(1.85)	.
-0.66	.	0.92***	.	.	10.8***	1.86***	7***	0.37
(0.58)	.	(0.32)	.	.	(1.74)	(0.48)	(1.83)	.
Model 3.								
1.29*	.	.	0.83**	.	10.6***	1.58***	.	0.29
(0.70)	.	.	(0.38)	.	(1.75)	(0.53)	.	.
-1.04*	.	.	2.03***	.	.	.	7.64***	0.33
(0.57)	.	.	(0.34)	.	.	.	(1.85)	.
-1.05*	.	.	0.89**	.	10.5***	1.68***	7.30***	0.37
(0.55)	.	.	(0.32)	.	(1.64)	(0.50)	(1.82)	.
Model 4.								
1.71**	.	.	0.50	-0.080	11.1***	1.61***	.	0.31
(0.79)	.	.	(0.38)	(0.40)	(1.72)	(0.53)	.	.
-0.53	.	.	1.82***	-0.070	.	.	7.22***	0.34
(0.59)	.	.	(0.34)	(0.33)	.	.	(1.77)	.
-0.60	.	.	0.68**	0.22	11.2***	1.73***	6.81***	0.38
(0.58)	.	.	(0.32)	(0.33)	(1.67)	(0.51)	1.76)	.
Characteristics only.								
.	.	.	.	.	13.7***	2.77***	.	0.080
.	.	.	.	.	(2)	(0.65)	.	.
.	.	.	.	.	.	.	6.48***	0.24
.	.	.	.	.	.	.	(1.86)	.
.	.	.	.	.	12.5***	2.07***	5.68***	0.31
.	.	.	.	.	(1.91)	(0.51)	(1.84)	.

Table 2.14: Panel regression results. The table shows results from panel regressions using all 14316 tranche-month observations. The dependent variable in all specifications is the monthly return over the risk-free rate, in basis points. For each factor combination I run four regressions: Without characteristics, and with ratings and WAL individually and jointly. Panel A contains regressions for a specification including no factors, as well as for models 0 and 1. Panel B contains Models 2 to 4. Standard errors are in parentheses, and stars indicate significance at the 5-percent (*) and 1-percent (**) level. All specifications included month fixed effects, and standard errors are clustered at the monthly level. For each factor, the cross-sectional standard deviation of betas is normalized to 1 in every period.

Panel A.												
TERM					1.22	-1.07	1.06	-1.00	1.23	-1.02	1.07	-0.98
					(0.70)	(0.66)	(0.68)	(0.64)	(0.71)	(0.66)	(0.69)	(0.63)
AutoAll									0.071	0.24	-0.090	0.068
									(0.38)	(0.37)	(0.38)	(0.37)
AutoLow												
AutoLH												
AutoHigh												
Wal		5.97**		5.34**		7.91**		7.16**		7.74**		7.09**
		(1.99)		(1.94)		(2.18)		(2.11)		(2.19)		(2.11)
BtoBBB			14.7**	14.0**			14.5**	14.0**			14.5**	14.0**
			(2.10)	(1.99)			(2.07)	(1.99)			(2.08)	(2.00)
AtoAA			3.09**	2.62**			2.91**	2.63**			2.88**	2.66**
			(0.57)	(0.50)			(0.51)	(0.50)			(0.50)	(0.50)
Const	-11.8**	-16.4**	-12.6**	-16.6**	-15.1**	-15.1**	-15.4**	-15.3**	-15.2**	-15.1**	-15.4**	-15.3**
	(5.7e-10)	(1.54)	(0.14)	(1.55)	(1.87)	(1.86)	(1.87)	(1.86)	(1.89)	(1.86)	(1.87)	(1.86)
Adj. R^2	0.365	0.377	0.387	0.396	0.368	0.378	0.389	0.397	0.369	0.378	0.389	0.397

Panel B.												
TERM	0.82	-1.47*	0.85	-1.30	0.96	-1.29	1.01	-1.10	1.08	-1.20	1.09	-1.00
	(0.72)	(0.71)	(0.71)	(0.69)	(0.69)	(0.66)	(0.68)	(0.64)	(0.70)	(0.64)	(0.68)	(0.62)
AutoAll												
AutoLow	1.90**	2.15**	0.89*	1.18**								
	(0.41)	(0.42)	(0.39)	(0.39)								
AutoLH					2.18**	2.05**	0.87**	0.85**	2.23**	2.11**	0.95**	0.97**
					(0.36)	(0.34)	(0.33)	(0.32)	(0.36)	(0.35)	(0.33)	(0.33)
AutoHigh									-0.33	-0.25	-0.16	-0.10
									(0.40)	(0.40)	(0.40)	(0.39)
Wal		7.77**		7.30**		7.75**		7.24**		7.79**		7.16**
		(2.18)		(2.14)		(2.15)		(2.11)		(2.16)		(2.11)
BtoBBB			13.0**	12.5**			12.9**	12.3**			12.7**	11.9**
			(1.94)	(1.88)			(1.97)	(1.87)			(1.93)	(1.81)
AtoAA			2.33**	2.06**			2.15**	1.79**			2.02**	1.61**
			(0.51)	(0.51)			(0.58)	(0.57)			(0.60)	(0.59)
Const	-13.6**	-13.1**	-14.5**	-14.0**	-12.3**	-12.0**	-14.3**	-13.8**	-12.5**	-12.1**	-14.4**	-13.8**
	(2.09)	(2.00)	(2.11)	(2.02)	(2.04)	(1.99)	(2.15)	(2.08)	(2.01)	(1.95)	(2.12)	(2.03)
Adj. R^2	0.376	0.386	0.390	0.399	0.378	0.387	0.390	0.398	0.379	0.388	0.391	0.398

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