The Pricing of Asset-Backed Securities and Households' Pecking Order of Debt*

Roland Füss[†] Dominik Meyland[‡] Stefan Morkoetter[§]

This version: October 2024

Abstract

This paper studies the role of households' pecking order of debt in the pricing and rating migration of U.S. consumer debt asset-backed securities (ABS). Our empirical results show that the household's delinquency on mortgage and auto loan increases spreads of ABS using these loan types as collateral. Increasing delinquency on credit card and student loans often lower spreads of ABS with other collateral. We argue that delinquencies on these types of loans in a household's loan portfolio provide liquidity to other loans. In contrast, rising delinquencies on mortgages, the first to be repaid in the pecking order, are an indicator of a severe shock spilling over to other loan types, triggering a simultaneous increase in ABS spreads. Furthermore, we find for residential mortgage-backed securities (RMBS) a lower probability of future rating downgrades in times of high mortgage delinquency. Thus, ratings are adjusted according to changes in the business cycle.

***Acknowledgements:** The authors are grateful for the many useful comments and suggestions from Marc Arnold, Martin Brown, Matthias Weber, Leonidas Rompolis and participants of the PhD seminar at the University of St.Gallen, the NTNU Business School Conference 2023, and the FEBS 2024 conference.

†Swiss Institute of Banking and Finance (s/bf), University of St.Gallen (HSG), Unterer Graben 21, 9000 St.Gallen, Switzerland; Swiss Finance Institute (SFI), Geneva, Switzerland; Research Fellow at the Center for Real Estate and Environmental Economics, NTNU Business School, Trondheim, Norway; Phone: +41 71 224-7055; Email: roland.fuess@unisg.ch.

‡Swiss Institute of Banking and Finance (s/bf), University of St.Gallen (HSG), Unterer Graben 21, 9000 St.Gallen, Switzerland; Phone: +41 71 224-7027; Email: dominik.meyland@unisg.ch.

§St.Gallen Institute of Management in Asia (SGI), University of St.Gallen (HSG), 110 Amoy Street #03-01, 069930 Singapore, Singapore; Phone: +65 68507-338; Email: stefan.morkoetter@unisg.ch.

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Abstract

This paper studies the role of households' pecking order of debt in the pricing and rating migration of U.S. consumer debt asset-backed securities (ABS). Our empirical results show that the household's delinquency on mortgage and auto loan increases spreads of ABS using these loan types as collateral. Increasing delinquency on credit card and student loans often lower spreads of ABS with other collateral. We argue that delinquencies on these types of loans in a household's loan portfolio provide liquidity to other loans. In contrast, rising delinquencies on mortgages, the first to be repaid in the pecking order, are an indicator of a severe shock spilling over to other loan types, triggering a simultaneous increase in ABS spreads. Furthermore, we find for residential mortgage-backed securities (RMBS) a lower probability of future rating downgrades in times of high mortgage delinquency. Thus, ratings are adjusted according to changes in the business cycle.

JEL Classification: G12, G24.
Keywords: Asset-Backed Securities (ABS); Asset Pricing; Credit Risk; Household Finance; Pecking Order.

1 Introduction

The pooling of loans into asset-backed securities (ABS) allows financial intermediaries to collateralize loans and sell them in different tranches to a broad base of investors. These transactions are segmented based on the characteristics of the underlying pool of assets. Each collateral pool is limited to one type of loan (e.g., mortgages) only. Loans taken out by households (e.g., mortgages, consumer loans, credit card loans, automotive loans) are a large collateral type within the area of asset-backed securities. For the year 2021, Bloomberg finds 40,271 ABS tranches issued by financial intermediaries in the four major consumer debt categories of residential mortgage-backed securities (RMBS), auto, student, and credit card loan-backed ABS, with a total outstanding amount of USD 3,065,676 mn. Due to the homogeneity of the asset pool (e.g., only mortgages) spill-over effects between different loan types on the individual household level are not reflected when assessing the underlying credit risk of a ABS transaction. This segmentation of different collateral types allows us to study whether the pricing and rating migration of ABS transactions reflect households' repayment hierarchy.

In case households have multiple loans outstanding, the question arises which loan(s) will be serviced first and which will become delinquent when the household is in financial distress. In particular, delinquency decisions release liquidity that can be used to continue servicing other loans that are considered more important. In this paper, we extend the existing literature on the pricing mechanism and rating migration of ABS by studying the impact of such household's delinquency decisions on the pricing and rating migration of U.S. consumer debt asset-backed securities (ABS). Households can choose from a variety of loan types to optimize their consumption and investment patterns.[1] Typically, households rely on different types of debt, such as mortgages as well as credit card, auto, and student

[1] In the third quarter of 2022 total household debt balances reached USD 16.51 trillion (see Federal Reserve Bank of New York (Fed, 2022)). For 2016, Braga, McKernan, and Hassani (2019) document that more than half of the U.S. consumers have credit card debt (61 %), followed by auto or retail loans (34 %). Mortgage debt has decreased from 29 to 26 % between 2010 and 2016 due to the great financial crisis, whereas during the same time student loans increased from 9 to 12 %.

loans, to finance their liquidity needs. When households get into financial distress, they have to decide which type of loan they will repay and on which one they are going to default. If this repayment hierarchy is created in a regular and consistent way, the household forms a pecking order. From an aggregated perspective, this pecking order reflects the delinquency decision of a representative household that has to service different loan types.[2] This payment (or delinquent loan) hierarchy is not static but depends on the state of the economy and the composition of loan types within a households' debt portfolio and may vary accordingly.

The different types of household loans are originated by financial intermediaries, which, in turn, pool and resell them via the securitization markets. These asset-backed securities are rated at least by one of the three major credit rating agencies, but are backed by different underlying collateral types (e.g., mortgages or auto loans). Yet, they receive the same credit rating, and thus, should be priced similarly by investors.[3] In this paper, we analyze whether and how households' decision making regarding the repayment hierarchy of household loans affects the pricing and rating migration of securitized debt contracts. Such a prioritization of loan repayments by households has become even more important since the global financial crisis of 2007/2009, with its massive loan defaults. Specifically, we study how households' liquidity provision due to a rebalancing of cash flows and risk spillovers among loan types affect the pricing of ABS spreads.

Our study contributes to the existing literature in the context of securitization transactions and the underlying pricing as well as rating dynamics (see, e.g., He, Qian, and Strahan, 2012; Efing and Hau, 2015). [4] We empirically uncover the impact of households'

[2]We use the theoretical findings on the micro-level to discuss the pecking order for a representative household. However, since we take the perspective of investors in these securitization markets and are interesting in the pricing of these assets, we do not consider households on the micro-level in our empirical analysis.

[3]The equality of credit ratings is a cornerstone in existing regulatory frameworks and is stated in section 938(a)83) of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. This equality in pricing was also emphasized by the president of the largest rating agency, Standard & Poor's (see Cornaggia, Cornaggia, and Hund, 2017).

[4]The impact of financial regulation as a driver of risk-taking by investors and institutions in ABS markets has been studied by Efing (2020).

preferences regarding delinquency rates across the four major types of household debt, namely, mortgages as well as credit card, auto, and student loans on the spreads of the structured debt collateralized with them. Moreover, we model the interaction between delinquency on the collateral of an ABS and delinquency on other loan types. In this way, we empirically represent an optimization problem of the household, whose decision to delinquency on a particular loan also affects the delinquency decision on other loans, for example, by freeing up liquidity. For this purpose, we construct an extensive database covering more than 47,000 ABS tranches issued in the period from 2003 to 2021. We use the new seriously delinquent balances, i.e. the flow into delinquency, as a proxy for the households' pecking order. In our estimation strategy, we include various ABS control variables (tranche characteristics, issuer and rating fixed effects), macroeconomic control variables, as well as the composition of households' debt balance. Our large database also overcomes the data limitations faced by previous empirical studies (e.g., Adelson and Bartlett, 2005; Fabozzi and Vink, 2012) to provide more robust estimates.

First, we find that a higher delinquency on the underlying asset leads to higher spreads in the corresponding ABS market for mortgages and auto loans (*direct channel*). Second, when the delinquency on mortgages is high, all four ABS markets suffer from significantly higher spreads. Consequently, an increasing delinquency on mortgages is an indicator that households are under water and all other loan types are also at risk. We construe this mechanism as *risk spillover channel.* We argue that mortgages are the most important loan type for households, thus normally paid first in the pecking order. However, a severe shock leads to a switch in the payment hierarchy of the households. Mortgage delinquency is therefore an indicator for a severe adverse shock. Third, we report that an increasing delinquency on credit card and student loans significantly reduces the ABS spread in another ABS market such as for mortgages and auto loans. We interpret this observation as *liquidity provision channel* due to delinquency on other underlying loan types and attribute this to the position of these loan types in the pecking order of the household. Lastly, risk spillover and liquidity provision effects due to households' cash flow rebalancing decision are all the more dominant the greater the proportion of the loan type in the portfolio of the household.

The assignment of credit ratings for different tranches involves rating agencies. These ratings provide the opportunity to compare the risk profiles of different tranches with other investments. Thus, ratings are a central part of the issuing process of structured debt. Ammer and Clinton (2004) and Fabozzi and Vink (2012) investigate the importance of ratings as a source of information in the pricing of structured debt. He, Qian, and Strahan (2012) examine the impact of issuer size on the pricing of mortgage-backed securities (MBS). Adelson and Bartlett (2005) provide an overview of ABS rating migration behavior of different asset classes, while Deku, Kara, and Marques-Ibanez (2022) estimate the drivers of rating migration with a focus on issuer reputation in the European ABS market.

To the best of our knowledge, no study has yet dealt with the question of whether households pecking order, mirrored in the delinquency decision, affects rating migration. Specifically, we analyze whether the spread inherent in expectation of market participants regarding the risk of the different collateral types is reflected in the rating migration of RMBS tranches. Based on a large RMBS rating migration database, we find that rating agencies' decision making reflects the direct channel and the liquidity provision channel.[5] We measure a reduced downgrade probability in the RMBS markets during times of high mortgage delinquency. We do not find that liquidity provision from the other asset markets reduces the RMBS downgrade probability. As expected, the ratings are adjusted pro-cyclical with the economy. This part of the analysis also extends the literature on the drivers of rating migration in the U.S. ABS market by controlling for various other factors, such as the subordination within a deal, rating shopping, or the size of a tranche. The results provide evidence that RMBS tranches issued by large issuers are affected by a higher downgrade probability. These findings add new angles to the perspective of ABS

[5] Due to limited data availability in the other asset markets, we study rating migration on the RMBS market only.

rating migration in the existing literature.[6]

The remainder of the paper is organized as follows. Section 2 discusses the theoretical background of households' pecking order and relates it to the theory of ABS pricing. In Section 3, we introduce the data used in our empirical analysis. Section 4 presents the methodology and estimation results. Section 5 concludes.

2 Theoretical Background

In this section, we provide the theoretical background that relates households' pecking order of debt to the pricing of ABS. This allows us to investigate whether the pecking order is reflected in the pricing mechanism of ABS. We first introduce existing literature on the pecking order of households' debt. Next, we develop a simple model to describe households' optimal delinquency decision based on an optimization problem. Furthermore, we introduce the existing literature about ABS pricing as well as rating migration on which we build up our empirical model frameworks. By relating these strands of literature, we derive our hypotheses regarding whether and how the pecking order affects the pricing and risk transmission, as well as the rating migration of securitized debt.

2.1 Households' Pecking Order of Debt

Households typically hold more than one type of debt, such as mortgages as well as credit card, auto, and student loans, to mention the most important ones (see Federal Reserve Bank of New York (Fed, 2022)). This debt can be categorized into two major groups: secured (mortgages and auto loans) and unsecured (credit card and student loans). When households hold different types of debt, they have to decide which type of loan they will pay back in case of financial distress. When such decisions are made in a regular and

[6]For instance, He, Qian, and Strahan (2012), Efing and Hau (2015) and Griffin, Nickerson, and Yongjun (2013) examine the impact that the relationship between ABS issuers and rating agencies has on ABS pricing and rating generation.

consistent manner, a pecking order of household debt is formed. Households' pecking orders across these different loan types gain in relevance in times of financial turmoil. For example, a large increase in defaults and delinquencies of U.S. households occurred during the recession in the wake of the global financial crisis 2007/2009.[7] The pecking order of debt represents the default order of a household that has to service different types of loans.

The existing literature provides evidence that there is a pecking order of the household, which depends on the economic condition. Cohen-Cole and Morse (2010) analyze the drivers of individual decisions between delinquency in mortgages and revolving credit accounts. The authors find that in case of individual liquidity concerns households may keep choosing delinquency on their credit card as a way to smooth consumption using household level data between 2006 and 2007. Andersson, Chomsisengphet, Glennon, and Li (2013) find similar results by focusing on differences between the pre- and post-financial crisis periods. Their study shows that after the peak of the financial crisis, subprime debtors are more likely to prioritize their credit card payments over their mortgage payments than before the global financial crisis. Following the basic "option model" of a mortgage, as described by Kau and Keenan (1995), borrowers should default if and only if they have negative equity in their home. A possible explanation is that house prices fell dramatically during the crisis, and consequently, borrowers' options for their homes deteriorated in value. According to Chan, Haughwout, Hayashi, and van der Klaauw (2016) households with negative equity in their home operate in this way and prioritize repaying their credit card.

Conway and Plosser (2017) report an increase of credit card prioritization during the global financial crisis compared to households' mortgage similar to Cohen-Cole and

[7] Mayer, Pence, and Sherlund (2009) provide an overview of the development of mortgage defaults in the U.S. caused by the global financial crisis. According to the Mortgage Bankers Association, delinquency rates (90 days or more past due) rose from 2.4 % in 2002 to 5.2 % in 2008.

Morse (2010) and Andersson, Chomsisengphet, Glennon, and Li (2013).[8] In contrast, Conway and Plosser (2017) document for the average household a larger prioritization of its mortgage compared to its credit card in the years 1999-2014. However, there is an increase in the average prioritization of the credit card and a decrease in the prioritization of the mortgage during the global financial crisis. Following the basic “option model” approach introduced by Kau and Keenan (1995) this behavior is understandable as households have an incentive to prioritize their mortgages during times when the overall value of their homes is increasing. This was the case during the majority of years investigated by Conway and Plosser (2017), whereas the global financial crisis let to lower real estate valuations resulting in negative equity position from a household’s perspective. In such a situation it is rationale for a household to change the priority of debt repayments (e.g., priority of credit cards). These findings support our argument that the pecking order of a household is not static but depends on the state of the economy. Moreover, the composition of households’ debt portfolio also shapes the delinquent debt hierarchy.

According to Andersson, Chomsisengphet, Glennon, and Li (2013), households were also increasingly exposed to credit shortages, leading to liquidity problems, which stopped them paying their mortgages as they prioritized credit card repayments for liquidity reasons to cover daily necessities (e.g., food). A similar finding is presented by Elul, Souleles, Chomsisengphet, Glennon, and Hunt (2010) showing that consumers’ illiquidity and negative equity in owned real estate trigger mortgage defaults. As long as the equity claim in the property is large enough, a rational household will sell the house on its own initiative to avoid a mortgage default. However, Mayer, Pence, and Sherlund (2009) show that in the years 2005 to 2007, more than half of newly originated subprime mortgages had a loan-to-value ratio of 100 percent. In this case, households quickly get into a situation in

[8]The study of Conway and Plosser (2017) is based on the New York Fed Consumer Credit Panel / Equifax (CCP). The individuals included in this panel must go delinquent at least on one type of debt while keeping at least one other loan. To predict the type of debt which is most likely repaid, the authors use Elo rating and symmetric logistic regressions. In contrast, we use newly seriously delinquency as a more direct measure for a households’ pecking order of debt. Interestingly, the delinquency rate shows a very similar pattern as the prioritization score of Conway and Plosser (2017).

which defaulting on a mortgage is rational. In summary, there is evidence of a household pecking order for a mortgage and a credit card loan depending on the economic condition of the household. This pecking order between the two assets is even more pronounced if the inherent option value of the mortgage is low.

Beside mortgages, auto loans usually make up another large debt position of a household (see Fed, 2022). Chan, Haughwout, Hayashi, and van der Klaauw (2016) find evidence for a repayment hierarchy between mortgages and auto loans similar to that between mortgages and credit cards if the property owners' home equity worsens. Interestingly, Conway and Plosser (2017) report for the average household that auto and mortgage debt are strongly prioritized, i.e. 10 times more likely to be paid over credit card debt in the period before 2007. The authors argue that borrowers lose less when defaulting on credit card compared to the two types of collateralized loans.[9]

However, there is only limited research that explored households' repayment decisions between auto and credit card loans. Following Cohen-Cole and Morse (2010) and Chan, Haughwout, Hayashi, and van der Klaauw (2016), one could argue that rational households in financial distress default on their auto loans to reduce their debt burden and smooth consumption when they have a negative equity claim in their car or simply prefer access to consumption via their credit card(s) over access to mobility. In contrast, Conway and Plosser (2017) find that auto loans are always prioritized over credit card debt during the entire period from 1999 to 2015. Ionescu and Ionescu (2014) provide a theoretical model for the interaction between credit card and student loans. Their model demonstrates a preference for a delay in student loan payments to smooth consumption by using a credit card. This result is in line with the finding of, e.g., Cohen-Cole and Morse (2010), who argue in a similar way to explain the payment hierarchy between mortgages and credit card loans. In contrast, the literature is silent on the default hierarchy between mortgage

[9]While prior to the recession mortgage and auto loan were equally prioritized, the pecking order not only reverses but also the difference in prioritization of the two loan types widens. In contrast, the debt payment prioritization between mortgage and credit card narrowed (see Conway and Plosser, 2017).

and student loans or auto and student loans. However, households may prefer to default on their mortgages and auto loans to preserve liquidity and reduce their debt burden. This can happen if a default on a student loan induces difficulties in consumption smoothing due to reduced access to the unsecured credit market (see Cohen-Cole and Morse, 2010 and Chan, Haughwout, Hayashi, and van der Klaauw, 2016).

In summary, the literature provides evidence that there is a pecking order that leads to a household repayment decision between different loan types. Yet, the empirical and theoretical analyses provide mixed results depending on the time period or the state of the economy, respectively. More precisely, the pecking order of debt depends on the economic environment to which the household is exposed and may therefore vary over time and economic cycles. Because default risk occurs according to the pecking order, defaults provide liquidity to service debt ranked at a more senior level in the household's individual pecking order. It is therefore important to consider the entire debt portfolio of a household and not only the pecking order of partial debt categories. In the empirical analysis (see Section 4), we fall back on observed delinquency rates to measure the state-dependent average pecking order of the household.

2.2 A Theoretical Model of Household's Pecking Order

We provide a basic household delinquency decision model as a primer for our subsequent empirical estimations.[10] Hereby we link shocks in the budget of a representative household to its delinquency decision forming a pecking order of debt. In the later empirical analysis, we argue that investors are using the delinquency decision and the formed pecking order as an indicator for the severity of the shock to which the average household is exposed. In this model, we focus on households which are already on the edge of a delinquency decision and that the household will not receive any further loans. Consequently, we abstract from wealth or equity claims, for which we control later in our empirical model. Without loss of

[10]See Campbell and Cocco (2015) who provide a more complex model on optimal mortgage default decisions.

generality, we assume that a stylized household has a monthly income stream generating a budget B which is used to serve principal and interest payments for two types of loans, a mortgage H and another loan type such as a credit card C, which cost $c_H H$ and $c_C C$.[11] Moreover the household may decide to use the budget for other consumption and costs of living L. We assume that the household choice of L is restricted by a lower boundary L^* to secure the minimum subsistence level. The household may opt to stop principal and interest rate payments on a loan which is modeled with the parameters D_H and D_C. This decision is binary. The living and loan costs are inputs to generate households utility $U(H, C, L)$. The utility provided by consumption of the different inputs is dependent on household preferences $\alpha = \{\alpha_H, \alpha_C, \alpha_L\}$. In this model the household lives just for one period and if the household stops payments for a loan it will lose the utility derived from the consumption financed by the related loan.[12] At the beginning of the period, the household observes its budget. A shock S (similar to, e.g., Ionescu and Ionescu (2014)) can hit the budget during this period. Accordingly, the household optimizes its utility:

$$\begin{aligned} \max_{D_H, D_C} U(H, C, L) &= \alpha_H H(D_H) + \alpha_C C(D_C) + \alpha_L L \\ \text{s.t.} \quad B - S &= c_H H(D_H) + c_c C(C_H) + L \\ \text{s.t.} \quad L &\geq L^* \quad . \end{aligned} \tag{1}$$

This optimization problem can be solved as follows. If the household does not face a budget shock ($S = 0$) it will simply serve the two loans if $\alpha_H H(D_H) \geq \alpha_L L$ and $\alpha_C C(D_C) \geq \alpha_L L$. This is the normal case, otherwise the household would not have taken the loan. However, if it faces a shock, i.e. $S = 1$, the household has to decide which expenditures are cut down. If the shock is $L - S \geq L^*$, then the household will cover the shock with a reduction of L. In contrast, if $L - S < L^*$ the residual has to be

[11] The assumption that the households loan portfolio consists out of two loans is a simplification. In our empirical analysis, we apply the idea of a utility maximizing household to a delinquency decision between four major loan types.

[12] For some loans, such as student loans, the utility lies in past consumption. However, delinquency on such loans can still result in a loss of benefit, e.g. through repossession or a lower credit rating, making it more difficult to obtain further loans.

covered by a delinquency decision. The household has the preference to keep the more important loan alive. Moreover, the household has to consider both the loan size and the associated costs. Thus, there are functions $D_H = f_{D_H}(c_H H, c_C C(D_C), L, \alpha, B, S)$ and $D_C = f_{D_C}(c_H H(D_H), c_C C, L, \alpha, B, S)$ describing household's delinquency decision. The household follows a pecking order to maximize its utility.

Large parts of the debt of private households are securitized after their origination and subsequently sold to investors via the underlying ABS structures In the following, we study if the beforementioned repayment hierarchy of households is reflected in the pricing of ABS. The described decision in case of a shock in the household's budget can be linked to the risk associated with an investment into an ABS tranche and is a key element in the pricing mechanism of ABS. Hence, we are not interested in the household decision itself but in the consequences for investors buying loans pooled in ABS.

In the theoretical model (1), the decision not to repay a loan also affects delinquency on other loan types. In our estimation strategy (see Subsection 4.1), this relationship is modeled by an interaction term between different delinquency types. The pricing mechanism of an ABS in our empirical model is driven by the delinquency on the ABS collateral and the interaction term. Furthermore, we estimate an additional model in which not only the interaction between different delinquency types drives ABS spreads, but also the outstanding loan amount which is affected by the delinquency decision.

2.3 The Pricing Mechanism of Asset-Backed Securities

The underlying credit risk is the cornerstone of the pricing mechanism of structured debt contracts as the collateral pool contains defaultable assets. This underlying risk can be priced either by rating-based reduced-form models (see, e.g., Duffie and Singleton, 1997, Duffie and Singleton, 1999, or Duffee, 1999) or by default probability-based models (see, e.g., Yawitz, 1977). These models fall back on basic discounted cash flow approaches to value assets at risk by considering risk-neutral probabilities of default.

The key problem of such models is the determination of these probabilities along the term structure. Typically, similar assets are grouped together to provide a larger sample for estimating the drivers of default probabilities. A homogeneous risk is therefore assumed within the group. In practice, the group definition and estimated probability are usually provided by a rating agency. A credit rating agency analyzes assets quantitatively and qualitatively, and groups them into rating classes with homogeneous, risk-neutral probabilities of default. It is assumed that all assets within a rating class bear the same risk (Cornaggia, Cornaggia, and Hund, 2017).

Because of its relevance for price formations several studies examine the impact of ratings on asset prices and the behavior of investors in financial markets. Weinstein (1977), Grier and Katz (1976), and Hand, Holthausen, and Leftwich (1992) find evidence that rating changes are important drivers of bond prices.[13] Fabozzi and Vink (2012) show that credit ratings are major drivers of the issuing spread of non-mortgage asset-backed securities. Due to the relevance of credit ratings in the issuing process of contracts, rating shopping by the issuer also plays an important role in the pricing mechanism. If an issuer is a frequent issuer of securities and delegates a large part of the underlying rating business to a particular rating agency, that rating agency may inflate its ratings to improve its relationship with that client or may delay future downgrades. He, Qian, and Strahan (2012) show that investors in mortgage-backed securities are pricing in the inherent risk that arises when large issuers benefit from inflated ratings.[14] Efing and Hau (2015) and Griffin, Nickerson, and Yongjun (2013) examine the impact of the strong ties between issuers and rating agencies on the generated ratings. They find that rating agencies favor issuers that have close business relationships with the agency.

Structured debt differs from other fixed-income products in terms of a diversified

[13]There is also a growing amount of literature addressing the impact of ratings on other asset classes such as stocks (see, e.g., Hand, Holthausen, and Leftwich, 1992 and Nandkumar and Rozeff, 1994) or spillover effects between different asset classes (see, e.g., Alsakka and ap Gwilm, 2012).

[14]There is also a number of studies analyzing rating shopping and rating inflation as a consequence of competition between rating agencies and the ability of issuers to purchase only the best rating (see, e.g., Bolton, Freixas, and Shapiro (2012) among others).

credit pool, tranching, and as a result of tranching, more complex contract work. Childs, Ott, and Riddiough (1996) examine the effect of pooling and tranching on the pricing of commercial mortgage-backed securities (CMBS). They show that pooling reduces the default risk for senior tranches due to diversification effects. However, reduced cash flow volatility due to diversification may reduce the value of the first-loss tranche. In addition, tranching leads to a decoupling of risk and cash flows, as losses are first covered by equity and junior tranches. Jobst (2005) notes that expected losses are typically covered by the equity tranche, while unexpected losses must be covered by more senior tranches, which is reflected in the differential pricing of the tranches.

In particular, when valuing mortgage-backed securities, it must also be taken into account that the underlying mortgages have an inherent prepayment option (see, for example, Copperstein, 2012). This option may reduce the value of the pooled mortgages. The calculation of the option value can be complex. In order to determine the option value, it is necessary to examine how future house price changes and interest rate shocks will influence households' behavior with regard to their mortgages (see, e.g., Copperstein, 2012).

Several empirical studies show that credit spreads within individual rating classes vary, and that investors do not believe in the uniform risk assessment of rating agencies, but treat risks within the same rating class differently (see, e.g., He, Qian, and Strahan, 2012). We contribute to this literature by investigating whether the debt pecking order of a household is reflected in the pricing of ABS. In the following, we use households' delinquency decision regarding different loan types as a proxy for the pecking order. We interpret the status "serious delinquency" as the outcome of the household's utility maximization problem described in Subsection 2.2. An increase in a particular loan delinquency rate, e.g. mortgage delinquency, is the consequence of more households choosing that particular delinquency in their optimization problem.

Our key variable for the pricing of an ABS tranche is the delinquency decision of the household regarding the underlying loan which is pooled and linked as collateral to the ABS. As a *direct channel*, delinquent loans will increase the spreads of ABS using this loan type as collateral. However, delinquency on other loan types does not affect the investor directly but provides information about the economic condition of the household if the investor assumes certain preferences α in the optimization problem introduced in Subsection 2.2. In case of a shock the household will try to keep loans providing more utility than others and will stop payments on less preferred loans. This causes a *liquidity provision channel* for the other more important loan types leading to reduced ABS spreads secured by these loans. However, if the household becomes delinquent on loan types which are more important, the investor assume that the household's budget has been hit by a severe shock. This causes a *risk spillover channel* to ABS using other loan types as collateral. In our empirical analysis, we aim at studying the *direct*, *liquidity provision*, and *risk spillover channel* of households' pecking order in the pricing of ABS. Depending on the position of the loan, which is used as collateral, in the pecking order, the channels described above affect the loan in the household's loan portfolio.

A household's pecking order not only affects the ABS pricing mechanism but also rating migration, particularly, rating downgrades. In the next subsection, we therefore describe how the household's pecking order influences ABS rating migration.

2.4 Pecking Order and Rating Migration

If the households' pecking order of debt influences ABS pricing it is natural to ask whether delinquency decisions also affect agencies' rating migration decisions. The pecking order and shifts in the pecking order caused by an increase in delinquency on a particular loan at the time of issuance provides investors with information about the economic state of households. However, in contrast to the pricing of ABS at issuance, the future development of the tranches is examined. If the pecking order indicates that households are able to service their preferred loans, i.e. those that provide a higher utility, and opt for delinquency on other, in terms of utility, less important loans, this may be reflected in lower rating migration probabilities for the ABS using the more important loans as collateral due to liquidity provision. At the same time, delinquencies on less important loans may not be sufficient to service more important loans in the longer term. In this case, rising delinquency rates on less important loans would be followed by rising downgrade probabilities for ABS backed by more important loans.[15] If an increasing number of households opt for delinquency on more important loans it is more likely to observe a shift in the pecking order. This indicates that more households are exposed to a severe shock S, i.e. find themselves in a poor economic state. This may already be included in the rating on the issue date, and thus, may affect future rating downgrade probabilities.

We study empirically the effects of delinquency decisions on rating downgrade probabilities in Subsection 4.2. According to Ammer and Clinton (2004) these downgrades will, similar to the findings of Weinstein (1977), Grier and Katz (1976), and Hand, Holthausen, and Leftwich (1992) for corporate bonds, negatively affect the value of the tranche. In a more descriptive study of rating migration frequencies of ABS with different types of collateral, Adelson and Bartlett (2005) find that credit card and student loan-backed securities have the lowest rate of negative rating migrations. Deku, Kara, and Marques-Ibanez (2022) examine the influence of issuer reputation on the probability of a rating downgrade and find a positive impact for issuer reputation, thus lower downgrade probabilities. In contrast, we propose a model framework to explore the effect of household's delinquency decision on ABS rating migration.

3 Data

We use manually collected data for U.S. mortgage and consumer loan-backed ABS tranches, rated by S&P and provided by Bloomberg for the period 2003 to 2021. Whereas ABS data

[15] In the later empirical analysis, we are able to distinguish between loans providing more or less utility based on the findings in the pricing mechanism of the ABS. We empirically test this mechanism in Subsection 4.1.

would have been available from 1989 onwards, we had to restrict our sample to the period from 2003 to 2021 due to availability of delinquency data for mortgage, auto and credit card loans. Student loan delinquency rates are only available for the period 2004 to 2021. We choose S&P-rated tranches because S&P, as it covers the largest share of tranches compared to the two other rating agencies, namely Moody's and Fitch. [16] We focus on privately issued tranches to rule out tranches that benefit from government support. Therefore, we exclude tranches that are rated by S&P but issued by the GSEs Fannie Mae and Freddie Mac.[17] In addition, we merge these data with rating migration information extracted from S&P's Rating Direct Database.

The dependent variable in our estimation models is the yield *Spread* in % of the tranches at issuance. Similar to He, Qian, and Strahan (2012), we calculate for fixed coupon tranches the spread as the difference between the coupon rate and the Treasury security with a maturity closest to the weighted average life (WAL) of the tranche. For very short maturities of less than one year, we use the interbank rate with the maturity closest to the WAL of the underlying tranche. If the tranche is a floater, the reset index is applied to calculate the spread of the tranche. We opt to use this definition of the spread, similar to He, Qian, and Strahan (2012), because issue price information is not available for many tranches. Therefore, a model based on estimated initial yields would significantly reduce the sample. However, we exclude zero coupon tranches to prevent the impact of misleading spreads. [18] We apply 99.5 % winsorization to avoid the impact of outliers.

The key information to uncover the effects of households' repayment hierarchy on the market for structured debt is the flow into serious delinquency across different loan types which is measured as new seriously delinquent balances in percent. We consider aggregated

[16]We acknowledge that our data sample might be prone to a rating bias induced by using S&P ratings only (e.g., overall, too conservative or too optimistic ratings compared to other rating agencies, such as Fitch or Moody's). However, we argue that split ratings are relatively rare (see He, Qian, and Strahan (2012)) and should be consistent when they exist.

[17]ABS tranches which are issued by GSEs benefit from the implicit government support of the issuing agencies.

[18]There are 3,513 zero coupon tranches in our large raw data set that are excluded.

households because ABS are derived from a securitized pool of loans and we also take the perspective of an investor in the ABS market. The delinquency reflects households' repayment preferences, and, because of its implied long-term consequences on financial health, the households' pecking order of debt. This data is provided by the Fed (see, e.g., Fed, 2022). Fed (2022) defines seriously delinquent balances as loans which are 90 or more days delinquent. Because data is available across all loan types for the period 2004 to 2021 the sample used in our main model specifications is reduced to this time period. Obviously, the flow into serious delinquency fluctuates over time. Figure 1 provides an overview of new delinquency for mortgages as well as credit card, auto, and student loans. We observe that the flow into delinquency of mortgages strongly increases as a consequence of the great financial crisis in 2008/2009. As a result of Covid-19, the Covid-19 Emergency Relief suspended payments on a large number of student loans and reduced interest rates to 0 % beginning in March 2020. This can be clearly seen in the evolution of student loan delinquency rates shown in Figure 1. In the household's optimization problem (1), this market intervention sets the cost of the affected loan to zero. The household responds with an adjusted delinquency decision causing a switch in the loan payment hierarchy and therefore in the pecking order.

[INSERT Figure 1 HERE]

Table 1 shows the summary statistics of the flow into serious delinquency for mortgages as well as credit card, auto, and student loans shown in Figure 1.[19] The data shows that student and credit card loans on average have a greater flow into serious delinquency than mortgages and auto loans. The average flow into serious delinquency is 5.77 % for

[19]Note that student loans differentiate from the other loan types in that they are originated by state governments. Because the fraction of student loans is small compared to the other assets, only a small number of ABS tranches are securitized. Braga, McKernan, and Hassani (2019) also mention that student loans are difficult to discharge in bankruptcy. Moreover, student loan holders can discharge their loans by filing for Chapter 7 or 13 bankruptcy and declare that repayment would cause undue hardship to them and their dependents. However, this decision must be made by court and can be challenged by creditors (Braga, McKernan, and Hassani, 2019). In sum, student loans differ from other debt classes in various ways, which might influence the pricing of this securitized debt.

credit cards and 8.04 % for student loans, while for mortgages and auto loans it is 2.71 % and 2.14 % respectively. The sharp increase in mortgage delinquencies during the financial crisis is reflected in the variable's wide range.

[INSERT Table 1 HERE]

The household's optimization problem (1) is driven by the outstanding loan amount which is affected by delinquency. To control for the loan amount we use the U.S. Survey of Consumer Finances data provided by the Fed. The survey is conducted every three years and contains detailed representative data about the financial situation of U.S. households. For the pricing of ABS, only the outstanding loan amounts of households that actually have to service a loan that serves as collateral are relevant, as well as the other loan types in the loan portfolio of these households. Therefore, based on the survey data, we calculate the conditional mean of the outstanding loan amount for each household loan used as collateral. Table 2 provides an overview of this loan amount data. For each type of loan that is used as collateral for an ABS, we can determine the loan portfolio held by the average household at time t. In Table 2, $Amt(m) \mid Bwr(l)$ is the conditional mean of outstanding loan m if the household holds the loan type l. For instance $Amt(Mortgage) \mid Bwr(Mortgage)$ is the average mortgage amount if the household has a mortgage, $Amt(Credit\ Card) \mid Bwr(Mortgage)$ is the average credit card loan amount if the household has a mortgage, and so on. For example, the average household with a mortgage has an outstanding mortgage amount of USD 368,200. At the same time, the average mortgage debtor has an outstanding credit card debt of USD 5,600, an outstanding student loan of USD 7,200 and an auto loan of USD 22,400. [20][21]

[INSERT Table 2 HERE]

[20]The student loan balance of the average mortgage borrower is relatively low due to the fact that the average mortgage borrower is older and has already paid off some of her student loan.

[21]For the sake of completeness, we also show the overall statistic $Amt(l)$. As expected, the average loan amount for the whole sample is smaller than the conditional loan amount $Amt(l) \mid Bwr(l)$ for all loan types l. This is because only households that actually have the corresponding loan are included in the calculation of the conditional loan amount.

ABS tranches possess a wide variety of characteristics that may influence the spread. Therefore, we add several variables to our model to control for tranche level characteristics. The variable *Subordination* refers to the ratio between a tranche and the amount offered in tranches that are junior to the respective tranche. Consequently, this variable measures the size of a tranche's loss buffer. WAL measures the weighted average lifetime of a tranche in years. The variable $Issuer\ Share$ is defined as the market share of an issuer in the previous year in relation to the principal amounts across all types of collateral. *Principal* is defined as the tranche offer amount in USD 100 mn and can be interpreted as a size measure. To control for differences between floater and non-floater tranches, we define a dummy variable $Floater$ coded 1 if the tranche is a floater tranche and 0 otherwise. Table 3 shows the summary statistics of the variables for all four ABS types which are analyzed in the following. We observe the largest average spreads in the RMBS market (148 basis points) and the smallest in the student loan ABS market (70 basis points).

[INSERT TABLE 3 HERE]

Furthermore, we match the tranche level data with a set of monthly financial and macroeconomic variables which may affect the valuation of ABS. In addition, institutions such as the Fed or government-sponsored enterprises (GSEs) can affect RMBS pricing. QE tracks the RMBS purchases programs of the Fed as the first difference of their RMBS holdings. GSE is a measure of GSEs' activities on the mortgage market and is defined as the first difference of GSEs' mortgage holdings in mortgage pools and on their balance sheets. The *Case Shiller* Index is used to control for the growth rate of house prices. It is important to control for the change in house prices because it may affect the default option in case of negative equity in the house (see Kau and Keenan, 1995). The valuation of ABS also depends on the general macroeconomic environment, which we control through a number of variables. Since GDP is only measured on a quarterly basis, we use industrial production growth (*Industrial Production*) as a monthly proxy. *Unemployment* tracks the seasonally adjusted unemployment rate. Changes in personal income is measured by the growth rate of the personal disposable income variable ($Income$). To control for existing wealth and wealth shocks, we add average net wealth ($Average\ Wealth$) of a household in the bottom 50 % of U.S. wealth distribution and changes in wealth ($Wealth$) as the growth rate of bottom 50 % wealth in the U.S. Moreover, we track inflation with the change in consumer price index CPI year by year and seasonally adjusted. The 90-day interbank rate (*Rate*) controls for the prepayment option value (Copperstein, 2012) as well as the loan costs. The financial and macroeconomic data are retrieved from the Federal Reserve Economic Data (FRED), St. Louis Fed. Table 4 provides summary statistics of all financial and macroeconomic variables. Table 5 provides an overview of the amount of the different S&P ratings at issuance for the tranches used in the estimation of our models across the different collateral types. In general, AAA tranches account for the majority of tranches across all four ABS types.

[INSERT TABLE 4 HERE]

[INSERT TABLE 5 HERE]

Based on the S&P's Rating Direct Database, we also have access to the rating migration data of ABS tranches. Using this data, we examine the probability of a rating downgrade. We define a rating downgrade *Down* as a binary variable which is coded 1 if we track a rating migration below the rating at issuance in a specified time window and 0 else. In the following, we focus only on RMBS rating migrations, because we only observe very few downgrades of auto, credit card and student loan-backed ABS. We focus on the time within 36 months after issuance. Moreover, in the later analysis we limit our sample to tranches with a maturity of at least three years to rule out a bias due to tranches which were repaid earlier than the specified time window. In total, we find 28,586 RMBS tranches which were downgraded with a probability of 29.38 % in the period 2003 to 2021. Table 6 provides an overview about the variable *Down*.

[INSERT TABLE 6 HERE]

4 Empirical Framework and Results

In this section, we present the empirical framework and discuss the empirical results regarding the effect of households' pecking order on the pricing mechanism (Subsection 4.1) of ABS as well as rating migration patterns (Subsection 4.2).

4.1 Does the Pecking Order Affect the Pricing of ABS?

To analyze the pricing effects of households' pecking order of debt, we specify the linear model in Equation (2) to explain the ABS spread ($Spread$) of the i tranches from issuer j with rating class k for a collateral l at time t. We estimate this model for the spreads of all four different consumer loan-backed ABS.

$$Spread_{i,j,k,l,t} = \beta_0 + \Omega_{i,l}(\beta_{1l}, \beta_{1lm}) + \beta_{2l}Amt(l) + \beta_3 X_i + \beta_4 \delta_t + \beta_5 \zeta_j + \beta_6 \lambda_k + \epsilon_{i,j,k,l,t}. \tag{2}$$

In these models, our main variable vector Ω contains the flow into delinquency of the collateralized consumer loan l as a proxy providing information about the delinquency decision making, and thus, the actual pecking order of the household.

$$\Omega_{i,l} = \beta_{1l} Del_l + \sum_{m \neq l}^{3} \beta_{1lm}(Del_l \times Del_m \times Amt(m)|Brw(l)). \tag{3}$$

The household may opt for loan delinquency in case of an adverse shock as shown in Subsection 2.2. ABS investors are only interested in the delinquency of the loan type which is used as collateral for the ABS they are investing in. Thus, if the household opt for delinquency on another loan type, this may also change investors' view on delinquency on the loan type used as collateral for the ABS due to risk spillover or liquidity provision. Therefore, we also estimate the effect of interaction terms between the ABS collateral's delinquency rate Del_l and the other three delinquency rate types Del_m.

The loan portfolio of the households is not static, but varies over time. However, it is possible that the size of the loan that is delinquent will influence whether there is liquidity provision or risk spillover to other loans in the loan portfolio of the household. Thus, we estimate also a model including the average outstanding amount of the different loan types. This amount is calculated as the conditional mean of outstanding loans if the household holds other loan types in addition to the collateral for the ABS considered, $Amt(m)|Brw(l)$. In our model in Equation (2), we also control for the average outstanding amount of the loan which is collateral for the corresponding ABS, $Amt(l)$. It is important to control for different sizes between delinquency shocks of loans, i.e. between the loan which is collateral and the loans which are not collateral for the ABS. The delinquency rates and the outstanding loan amounts are estimates. Therefore, we apply non-parametric bootstrapped standard errors based on 10,000 resampling runs with replacement in all models.

Similar to He, Qian, and Strahan (2012) and Fabozzi and Vink (2012), we also control for the rating class (λ_k) to avoid comparing investment grade versus junk tranches. Moreover, we include issuer fixed effects (ζ_j) to control for unobserved heterogeneity at the issuer level. Unlike He, Qian, and Strahan (2012) and Fabozzi and Vink (2012), we cannot use time-fixed effects, since they absorb the delinquency decision of the household measured in $\Omega_{i,l}$. Instead, we use the vector δ_t that contains the variables QE, GSE, $Case\ Shiller$, $Industrial\ Production$, $Unemployment$, $Income$, CPI, $Rate$, $Wealth$ and $Average\ Wealth$, described in Section 3, to control for the financial and macroeconomic environment. This is important to ensure that the estimated effects for $\Omega_{i,l}$ are not biased since ABS investors use this information about the business cycle at the time of issuance for their pricing. In the households' optimization problem (1), we abstract for simplicity from many parameters which may affect households' delinquency decision. In our model, we control for changes in household's income ($Income$), average net wealth ($Average\ Wealth$) of a household in the bottom 50 % of the U.S. wealth distribution. Moreover, we measure changes in wealth ($Wealth$) as the growth rate of bottom 50 % wealth in the U.S. The household may also adjust delinquency decisions in dependency of its employment status which is tracked by the monthly unemployment rate ($Unemployment$).

In the RMBS pricing model, the vector δ_t is also important to track information about the inherent prepayment option of the household, that may affect the pricing of RMBS tranches (see, e.g., Copperstein, 2012). Investors can use these macroeconomic variables to forecast households' behavior regarding prepayment in order to determine the value of this option for each RMBS vintage year. Moreover, we control for the RMBS purchases of the Fed in the RMBS pricing model. Fed purchases focus on agency RMBS (QE). Meyland (2024) reports that GSE purchases affect the pricing of private-label RMBS issued by commercial banks which are able to sell mortgages to the GSEs. In this study, we do not only focus on issuers with a retail banking business but also allow for the possibility of selling mortgages to GSEs. However, as we cannot a priori rule out spillover effects from the agency MBS market into the private label RMBS market, we include the variable GSE in our RMBS pricing model to control for changes in the volume of directly or indirectly held mortgages by GSEs.

To control for differences between the tranches, vector X contains the tranche characteristics as additional control variables. We include $Subordination$ to control for the risk buffering effect of tranches that are junior to the respective tranche. We expect the level of subordination to have a negative impact on the spread. The tranches cover different debts with various maturities. Thus, we add the weighted average life (WAL) of a contract because the tranche's credit risk increases the longer it takes to recoup the principal.

Following the existing pricing literature (see, e.g., He, Qian, and Strahan, 2012 and Fabozzi and Vink, 2012), we control for rating shopping and the potential impact of issuer size by including the variable $Issuer\ Share$, which is defined as the lagged ratio of the total amount of structured debt issued by an issuer divided by the total amount of structured debt issued in the same year. In addition, we consider the *Principal* of the tranche to partial out tranche size effects. Furthermore, we add separate intercepts for the different coupon types (floater and fixed) by including the variable *Floater* in all regressions.

Table 7 provides the estimates of the full model for RMBS in Panel A, as well as the coefficients for the main variables for auto ABS, credit card ABS, and student ABS in Panels B to D, respectively.[22] The estimates of loan delinquency on the pricing of ABS which uses this loan type as collateral can be interpreted as the direct channel of households' pecking order in Model (1). The spillover effects from households' delinquency decision on other loan types can be categorized by the signs of the interaction terms in Models (2) and (3). Conceptually, the spillover effects change the marginal effect of the direct channel. A negative sign indicates liquidity provision. Delinquency on this loan type frees up liquidity on the household level and thus reduces the default probability of the other loan types (e.g., mortgages). The household therefore follows a debt prioritization that enables it to continue servicing the loan types on which the household did not default. Increasing defaults of households in one credit category have a positive impact on the default probability of other loan types hold by households at large. As a consequence, we see a reduction in ABS spreads in Models (2) and (3). However, a positive sign indicates a risk spillover. Households face a severe adverse shock which results in delinquency on loans that are usually paid first in the pecking order and investors increase the respective ABS spreads. The severe shock forces households to adjust their debt prioritization. Consequently, we observe an adjustment in the pecking order of the household.

[INSERT TABLE 7 HERE]

We find highly significant positive effects of the direct channel on RMBS and auto ABS markets for model specification (3) in Panels A and B, respectively, of Table 7. These

[22]The full model specifications for auto ABS, card ABS and student ABS are provided in Tables A.1 to A.3 of the Internet Appendix.

spreads increase in case of delinquency on loans used as their collateral. Interestingly, we do not find the direct channel on the credit card and student loan ABS markets (see Panels C and D of Table 7). Moreover, we do not detect spillover effects of delinquency from auto or student loans on credit card ABS in Panel C. However, in case of increasing mortgage delinquency our findings provide evidence of increasing spreads, indicating a risk spillover channel. This risk spillover channel is also present in student and auto loan ABS markets. We also find the risk spillover channel in place for auto loan delinquency in the RMBS and student loan ABS market, while the liquidity provision channel can be observed for the other two delinquency types in these markets.

Our model identifies the relations between the different loan delinquency types. The results can be interpreted as a realization of investors' assumed household's pecking order. Our findings provide evidence that investors assume that mortgages are the most important loan type for households and are usually served first and therefore also placed first in the pecking order. Thus, an increasing mortgage delinquency is an indicator for a severe adverse shock causing risk spillovers in all other ABS markets. However, investors assume that credit card and student loans are relatively less important for households, and thus, placed last in the pecking order. Hence, delinquency provides liquidity in many cases and investors do not assume a severe adverse shock. Interestingly, we do not find the direct channel for these loan types. This suggests that investors assume that such delinquency is not sufficient on its own, or does not occur alone, however, e.g., together with mortgage delinquency.

A comparison of these estimates with the sparse model specification (2) shows that the outstanding loan amount which is affected by the delinquency has an impact on the detected channels. Thus, controlling for loan amount eliminates the significance of the direct channel in the student loan ABS model (see Panel D of Table 7). The size of the channels is also influenced by the outstanding loan amount. This can be attributed to the household's optimization problem described in Subsection 2.2. Investors consider not only the pure delinquency decision, but also the loan amount involved.

To study the combined marginal effects of loan delinquency, we estimate the average marginal effects of model specification (3). Table 8 reports the results. The estimates show that the uncovered liquidity provision and risk spillover channels are economically significant. The average marginal effects of the direct channel can be interpreted as the combined effect of all three channels in the model. We do not find that the liquidity provision and risk spillover channels change the direction of the detected direct channels. However, a comparison of the direct channel on the RMBS market (see Panel A of Table 7) with the combined effect in Table 8 shows that the liquidity provision channel dominate the detected risk spillover channel as the combined marginal effect is smaller than the estimated direct channel. In the direct channel an increase of mortgage delinquency increases RMBS spread by 125.9 basis points while the average marginal effect including the other two channels is 78.1 basis points. The same applies to the auto loan ABS market (Panel B of Table 7). These differences are significant at the 95 % level. As we have not found a direct channel in the credit card and student ABS markets, we can dispense with further analysis here. Furthermore, as anticipated, the magnitude of the observed channels is influenced by the size of the loan impacted by the delinquency decision. We observe significant marginal effects of the conditional loan amounts, aligning with the direction of the respective delinquency decision rate.

[INSERT TABLE 8 HERE]

Our findings for the other tranche characteristics in model specification (3) of Table 7 for RMBS (Panel A) indicate that floater tranches have highly significantly larger spreads than non-floater tranches. This can be explained by the fact that interest rates on pooled mortgages are fixed for a longer period of time, while investors bear the interest rate risk on the refinancing side, for which they have to be compensated by issuers with higher spreads. *Subordination* significantly reduces the spreads in the RMBS which is a direct consequence of the risk buffering effect of subordinated debt in the waterfall structure of an ABS. We do not report significant effects of the WAL in the RMBS market. In contrast to He, Qian, and Strahan (2012), our findings do not provide evidence for an impact of the *Issuer Share* on RMBS. However, the analyzed time period differs from He, Qian, and Strahan (2012), because we also include observations after the financial crisis. The size of the tranche, its *Principal*, has a highly significant negative impact on the spread of tranches in the RMBS market. Generally, a significant negative estimate can be explained by lower search costs due to the higher number of potential investors. These results are consistent with existing evidence, such as Chen, Lesmond, and Wei (2007) and Helwege, Huang, and Wang (2014), who analyze the influence of offered amounts on the pricing of newly issued bonds. In the other ABS markets (see Tables A.1 to A.3 in the Internet Appendix) we find differing results for *Floater*, WAL, *Issuer Share* and *Principal*. These differences can be attributed to differences between the ABS market data sets for the individual tranche characteristics.

We find evidence for a highly significant negative effect of the *Case Shiller* index across all considered ABS markets. This is not surprising as house price appreciation provides additional funds to prevent loan delinquency. Our findings for inflation are twofold. We find for the RMBS a highly significant negative effect but across all other markets a positive effect. This can be attributed to the special nature of real estate as an investment. Existing research, e.g., Anari and Kolari (2002) provides evidence that real estate investments are a hedge against inflation. This results in a budget stabilization for households owning real estate properties. However, our findings for the consumption good loans provide evidence that lenders or ABS investors are exposed to a higher delinquency risk if inflation increases as households face stricter budget constraints due to a price shock.

Moreover, we find a significant negative effect of industrial production on the spreads in the credit card and student loan ABS market. Interestingly, we do not detect such outcomes for auto loan backed ABS and the RMBS market. However, we do find that decreasing unemployment rates reduce spreads in these markets and also in the market for student loan ABS. As expected improved economic conditions reduce spreads in ABS markets. The estimates for the different wealth variables show that positive wealth shock ($Wealth$) reduce spreads in all ABS markets besides the credit card ABS market. Interestingly, we report that $Average\ Wealth$ is associated with increasing spreads in the RMBS and student loan market. In the RMBS pricing model, we further find a negative impact of QE on RMBS prices, which provides evidence that the purchasing programs have the intended effect. However, we do not report an impact of GSE purchasing programs.

The pricing of ABS depends on the available information at issuance. While information on delinquency rates and tranche characteristics is available to informed investors at all times, it is quite possible that investors process macroeconomic data with a time lag.[23] Therefore, as a robustness check, we have re-estimated all models in all markets with macroeconomic control variables lagged by one month. The estimates are shown in Tables A.4 to A.7 in the Internet Appendix. We find that the lag structure does not affect these estimates. The marginal effects are reported in Table A.8 of the Internet Appendix.

Our results of households' delinquency decisions are important for investors and policy makers and document that the pecking order matters. The detected liquidity provision channel shows that policy makers do not always need to intervene in the event of a financial shock. However, policy makers should be aware of delinquency shifts towards mortgage delinquency as this leads to increasing spreads in ABS markets using other loan types as collateral and may affect financial market stability.

4.2 Does the Pecking Order Affect the Rating Migration of ABS?

In the next step, we examine the effect of households' delinquency decision making on the rating migration of the ABS tranches adding new insights to the existing ABS rating

[23]Delinquency rates can be purchased by data providers such as Equifax, which is also the data provider of the Fed. All tranche characteristics are provided at issuance by the issuer.

migration literature (see, e.g., Adelson and Bartlett (2005) and Deku, Kara, and Marques-Ibanez (2022)). We apply a Logit model according to Equation (4) in which we analyze the downgrade probability of a tranche with the downgrade definition described in Section 3. The model is defined as:

$$Pr[Down_{i,j,k,k,t} = 1] = \frac{e^{(\beta_0+\Omega_{i,l}(\beta_{1l},\beta_{1lm})+\beta_{2l}Amt(l)+\beta_3 X_i+\beta_4\delta_t+\beta_5\zeta_j+\beta_6\lambda_k)}}{1+e^{(\beta_0+\Omega_{i,l}(\beta_{1l},\beta_{1lm})+\beta_{2l}Amt(l)+\beta_3 X_i+\beta_4\delta_t+\beta_5\zeta_j+\beta_6\lambda_k)}} \ . \tag{4}$$

Households delinquency decision making is tracked in $\Omega_{i,l}$. In addition, we control for the same tranche characteristics (X_i) as well as the macroeconomic environment (δ_t), the rating class (λ_k) and the issuer (ζ_j) as in the baseline model of Equation (2). The standard errors are bootstrapped with 10,000 runs. Table 9 reports the estimated coefficients for RMBS. We cannot estimate models for the other collaterals due to limited observations. The average marginal effects of the interaction terms are reported in Table 10.[24]

[INSERT Table 9 HERE]

[INSERT Table 10 HERE]

The findings for the average marginal effects provide evidence that the initial rating at issuance are affected by the delinquency decision of the household. However, the results do not reflect the findings of the pricing model discussed in Subsection 4.1, but show that the sign of the coefficients for the direct and liquidity provision channels have reversed. Increasing delinquency on mortgages reduces future downgrade probability, while credit card and student loan delinquency increases the downgrade probability of RMBS. Therefore, the risk of future downgrades reduces. If the agency perceives this adjustment in the pecking order of the household, i.e. due to a severe shock, this is taken into account in the rating at the time of issuance. This goes so far that no further downgrades are necessary after issuance. And once households are in that poor economic state, the ratings

[24] The magnitude of the interaction effects in our nonlinear models are corrected by the approach suggested by Ai and Norton (2003).

improve in the future. The rating adjustment based on the direct channel is pro-cyclical with the economy. Interestingly, we do not find a significant effect of auto loan delinquency. In contrast, there is a larger probability of downgrades if households try to save liquidity due to delinquency on the credit card or student loans. Hence, we conclude that such delinquency decisions reduce spreads in the short term (see Table 8), but that the liquidity provision is not sufficient to reduce the risk of rating downgrades in the long term.

The other estimates shown in Table 9 can be interpreted directly. Although these are only side results, they add to the existing knowledge of the drivers of rating migration of RMBS due to the larger dataset we used. We find that the WAL increases the downgrade probability. This can be explained by the fact that investments with a larger WAL represent a risky investment over a significantly longer period of time, which increases the downgrade probability. The finding for the $Issuer\ Share$ which increases the downgrade probability extends existing research (Efing and Hau, 2015, Griffin, Nickerson, and Yongjun, 2013, and He, Qian, and Strahan, 2012) by reporting that issuers in the role of important commissioners may benefit from rating shopping. Consequently, they improve ratings for their issued tranches. However, such advantages diminish in subsequent periods. Interestingly, larger tranches with larger *Principal* benefit from reduced downgrade probability. The findings for the macroeconomic variables mainly mirror the expectation that the rating migration probability is reduced due to improved economic conditions such that, e.g, an increase in wealth ($Wealth$ and $Average\ Wealth$) reduces the downgrade probability while higher unemployment rates increase the downgrade probability. The findings for $Case\ Shiller$ and $Income$ can be traced back to the downgrades in the wake of the global financial crisis. The macroeconomic variables can be interpreted as additional control variables for the business cycle. However, the rating migration decisions are conducted within the following 36 months. Thus, a robustness check for lagged macroeconomic variables is not necessary.

5 Conclusion

In this paper, we analyze whether the pricing and rating migration of ABS tranches reflect households' pecking order in terms of their different loan types. We link a simple delinquency decision model of a representative household to a factor model, in which we examine the impact of households' delinquency decisions on ABS pricing. Empirically, the new seriously delinquent balances form a pecking order of debt based on the economic state of the households. Using an extensive database of ABS tranches, we find that loan delinquency increase the spreads of ABS using this loan type as collateral. Moreover, we study the effect of households decision making between delinquency in one and other loan types. We report that an increase of households' mortgage delinquency will always increase the spreads of ABS using other loan types as collateral. There is a risk spillover channel from the mortgage market to other loan types. We argue that investors assume that maintaining the mortgage is of utmost importance for households. However, if more households opt for delinquency on mortgages a shift in the pecking order can be observed and attributed to a large adverse shock which is reflected in the pricing mechanism of ABS.

In contrast, we find evidence that delinquency on other loan types, credit card and student loans, often reduces spreads in other ABS markets. This is due to a liquidity provision channel from one loan type to another in case of delinquency. The loan delinquency frees up liquidity that can be used to repay other types of debt. Thus, ABS using these other debt types as collateral benefit from reduced spreads. The size of the different channels increases with the amount of debt outstanding that is the subject of the delinquency decision.

Our results also confirm the spread-reducing effect of subordination in the RMBS and auto ABS markets. However, our results do not support existing research on the pricing of the issuer size on the RMBS market. As expected, we find that spreads decrease in better macroeconomic states. Moreover, our findings provide evidence that inflation hedge characteristics of real estate properties can also be found on ABS markets.

Furthermore, we study the impact of households delinquency decisions and the formation of the pecking order on the rating migration of RMBS tranches. We find evidence for a reversed effect of the pecking order. Ratings in times of higher mortgage delinquency benefit from a reduced downgrade probability, indicating that the ratings are assigned accordingly to the business cycle. However, the liquidity provision channel triggers a larger downgrade probability. Thus, liquidity provision is not sufficient to avoid future downgrades. Moreover, our findings extend existing research about the relationship between large issuers and rating agencies indicating that large issuers may benefit from better ratings due to rating shopping. However, this benefit diminishes in subsequent periods.

Our findings are important for policy makers. The pecking order of the household matters and delinquency is not always a severe problem for ABS markets. As in many cases, delinquency provides liquidity to other loan types and reduces the spreads on ABS using other loan types as collateral. However, if mortgage delinquency raises, policy makers should be aware of spillover effects to ABS markets using other loan types as collateral, even if the delinquency decision of the household regarding these types of debt is unaffected.

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Tables

Table 1: Summary Statistics: New Seriously Delinquent Balances

This table provides summary statistics of the quarterly variables that describe the percentage of new seriously delinquent (*Del.*) balances for mortgages, as well as credit card, auto, and student loans. The delinquency data for mortgages, credit card and auto loans are available for the years 2003 to 2021 and the data for student loan delinquency are available for the years 2004 to 2021. This data is provided by the New York Fed Consumer Credit Panel/Equifax. To match the frequencies between these quarterly data and the tranche characteristics (see Table 3), we fill in missing values between quarterly observations with the previous observation. Quarterly observations are given for each loan category. *S.D.* denotes the standard deviation, Min and Max are the minimum and maximum value.

	Mean	S.D.	Min	Max
Del. Mortgage	2.71	2.21	0.27	8.35
Del. Credit Card	5.77	2.08	3.22	10.96
Del. Auto Loan	2.14	0.51	1.52	3.48
Del. Student Loan	8.04	2.30	1.02	10.54
Observations	72			

Table 2: Summary Statistics: Outstanding Loan Amount

This table provides summary statistics of the mean of yearly outstanding loan amounts in USD 10,000 provided by the U.S. Survey of Consumer Finances for mortgages, as well as credit card, auto, and student loans for the time period 2003 to 2021. The survey is conducted every 3 years. $Amt(m) \mid Bwr(l)$ is the conditional mean of the outstanding loan m if the household holds the loan type l. For the sake of completeness, we also show the overall statistics $Amt(l)$ for all loan types. Yearly observations are filled with the previous value over each three-year period. The raw data is provided by the Federal Reserve. $S.D.$ denotes the standard deviation, Min and Max are the minimum and maximum value.

	Mean	S.D.	Min	Max
Amt(Mortgage) | Bwr(Mortgage)	36.82	3.24	30.12	41.70
Amt(Credit Card) | Bwr(Mortgage)	0.56	0.12	0.43	0.78
Amt(Student) | Bwr(Mortgage)	0.72	0.28	0.23	1.05
Amt(Auto) | Bwr(Mortgage)	2.24	0.68	1.12	3.09
Amt(Auto) | Bwr(Auto)	6.89	2.03	3.64	9.79
Amt(Mortgage) | Bwr(Auto)	16.58	2.17	12.25	19.93
Amt(Student) | Bwr(Auto)	0.96	0.32	0.38	1.33
Amt(Credit Card) | Bwr(Auto)	0.57	0.13	0.43	0.82
Amt(Credit Card) | Bwr(Credit Card)	0.94	0.17	0.78	1.24
Amt(Auto) | Bwr(Credit Card)	1.12	0.07	1.01	1.21
Amt(Student) | Bwr(Credit Card)	0.99	0.35	0.39	1.40
Amt(Mortgage) | Bwr(Credit Card)	13.61	2.46	10.35	18.38
Amt(Student) | Bwr(Student)	3.68	0.74	2.21	4.67
Amt(Mortgage) | Bwr(Student)	11.64	2.03	8.18	15.66
Amt(Credit Card) | Bwr(Student)	0.59	0.18	0.39	0.94
Amt(Auto) | Bwr(Student)	1.09	0.15	0.79	1.30
Amt(Mortgage)	15.59	2.17	13.02	19.60
Amt(Auto)	2.09	0.62	1.03	3.03
Amt(Credit Card)	0.35	0.07	0.27	0.48
Amt(Student)	0.60	0.23	0.21	0.85
Observations	19			

Table 3: Summary Statistics: Tranche Characteristics

This table provides summary statistics of the tranche characteristic variables used in the estimation models for the different ABS types. *Spread* is the difference between tranche's coupon and the corresponding risk-free rate measured in %. *Floater* is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. *WAL* denotes the tranche's weighted average life in years. *Issuer Share* is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Observations indicate the number of tranches. *S.D.* denotes the standard deviation, *Min* and *Max* are the minimum and maximum value.

	Mean	S.D.	Min	Max
RMBS				
Spread	1.48	2.46	-3.63	39.18
Floater	0.29	0.45	0.00	1.00
Subordination	0.04	0.08	0.00	0.99
WAL	5.57	3.32	0.00	58.88
Issuer Share	0.06	0.06	0.00	0.21
Principal	0.70	1.46	0.00	48.13
Observations	36,066			
Auto Loan ABS				
Spread	1.30	1.37	-2.55	13.03
Floater	0.09	0.29	0.00	1.00
Subordination	0.23	0.21	0.00	0.93
WAL	2.58	1.24	0.17	15.30
Issuer Share	0.02	0.02	0.00	0.19
Principal	1.60	1.98	0.02	29.05
Observations	7,921			
Credit Card ABS				
Spread	0.93	1.74	-0.02	20.00
Floater	0.63	0.48	0.00	1.00
Subordination	0.05	0.10	0.00	0.90
WAL	4.31	2.09	0.41	19.95
Issuer Share	0.02	0.04	0.00	0.19
Principal	4.70	5.06	0.02	50.00
Observations	1,214			
Student Loan ABS				
Spread	0.70	0.93	-3.18	10.45
Floater	0.85	0.36	0.00	1.00
Subordination	0.15	0.23	0.00	0.97
WAL	6.71	4.11	0.31	19.99
Issuer Share	0.03	0.03	0.00	0.11
Principal	3.00	2.90	0.00	39.64
Observations	1,396			

Table 4: Summary Statistics: Macroeconomic Variables

This table provides summary statistics of macroeconomic variables for the U.S. on a monthly frequency for the period 2003 to 2021 which are used as control variables in the estimation models. The data is provided by the FRED database. *QE* is the first difference of Fed MBS holdings (in USD bn). *GSE* is the first difference of GSE mortgage holdings (pool and balance sheet in USD bn). *Case Shiller* is the growth rate of the Case Shiller Index. *Industrial Production* is the growth rate of the industrial production. *Unemployment* is the seasonally adjusted unemployment rate. *Income* is the growth rate of personal disposable income. *CPI* is the core sticky inflation rate. *Rate* is the 90-day interbank rate. *Wealth* is the net wealth growth rate. *Average Wealth* is the average wealth of a household. Observations are monthly time series for each macroeconomic variable. *S.D.* denotes the standard deviation, *Min* and *Max* are the minimum and maximum value.

	Mean	S.D.	Min	Max
QE	12.07	33.90	-33.60	229.21
GSE	75.85	64.88	-13.21	251.16
Case Shiller	0.33	0.85	-2.30	2.30
Industrial Production	0.05	1.32	-13.40	6.50
Unemployment	6.14	2.07	3.50	14.70
Income	0.21	2.48	-15.30	22.70
CPI	2.22	0.54	0.67	3.48
Rate	1.52	1.69	0.09	5.49
Wealth	1.55	6.86	-19.31	13.13
Average Wealth	21.75	11.24	6.63	51.40
Observations	216			

Table 5: Summary Statistics: Ratings

This table provides an overview of the number of different S&P ratings at issuance in our dataset between 2003 and 2021 for RMBS, credit card ABS, and auto ABS. The data is grouped by ABS type. Student ABS are tracked between 2003 and 2021. S&P provides rating categories ranging from AAA to D.

	RMBS	Credit Card ABS	Auto ABS	Student ABS
AAA	23,862	692	4,062	1,007
AA+	882	42	199	175
AA	2,788	49	846	77
AA-	496	21	60	10
A+	577	23	171	6
A	2,426	180	951	96
A-	541	2	46	1
BBB+	522	6	90	2
BBB	2,217	177	794	22
BBB-	580	7	35	0
BB+	60	1	34	0
BB	382	11	330	0
BB-	77	3	189	0
B+	68	0	37	0
B	322	0	71	0
B-	62	0	6	0
CCC+	0	0	0	0
CCC	58	0	0	0
CCC-	0	0	0	0
CC	146	0	0	0
C	0	0	0	0
D	0	0	0	0
Observations	36,066	1,214	7,921	1,396

Table 6: Summary Statistics: Rating Migration

This table provides summary statistics of S&P RMBS downgrades (*Down*). *Down* is a binary variable coded 1 if the tranche's rating is downgraded below the original rating at issuance within 36 months after issuance, and 0 otherwise. Observations indicate the number of rating migrations.

Year	0	1	Total
2003	4,007	3	4,010
2004	5,490	11	5,501
2005	6,884	415	7,299
2006	1,191	3,724	4,915
2007	127	3,975	4,102
2008	28	129	157
2009	5	2	7
2010	8	5	13
2011	0	3	3
2012	37	0	37
2013	322	0	322
2014	364	0	364
2015	234	0	234
2016	55	11	66
2017	109	41	150
2018	284	48	332
2019	339	27	366
2020	405	4	409
2021	306	0	306
Observations	20,195	8,398	28,586

Table 7: The Pricing of ABS and the Pecking Order

This table shows OLS regressions of the *Spread* of privately issued RMBS as well as Auto, Credit Card, and Student ABS tranches on households' delinquency preferences (Ω). *Del.* stands for new seriously delinquent balances (in %) for mortgages, as well as credit card and auto loans for the sample period 2003 to 2021 and for student loans for the sample period 2004 to 2021. The full model specifications for Auto, Credit Card, and Student ABS are provided in the Internet Appendix (see Tables A.1, to A.3). The data contains the mean outstanding mortgage amount (e.g., $Amt(Mortgage) \mid Bwr(Mortgage))$) of held loans and the conditional mean of other loans if the household holds the respective loan ($Amt(m) \mid Bwr(Mortgage)$). *Floater* is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. WAL denotes the tranche's weighted average life in years. $Issuer\ Share$ is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Financial and macroeconomic control variables are those listed in Table 4. The model specifications include *issuer and rating fixed effects*. t-statistics are in parentheses. We use non-parametric bootstrapped standard errors on 10,000 resampling runs with replacement. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Spread (1)	Spread (2)	Spread (3)
Panel A: The Pricing of RMBS and the Pecking Order			
Del. Mortgage	0.239***	1.996***	1.259***
	(5.91)	(7.89)	(8.06)
Del. Mortgage × Del. Auto Loan		-0.086	
		(-1.09)	
Del. Mortgage × Del. Credit Card Loan		-0.080***	
		(-4.28)	
Del. Mortgage × Del. Student Loan		-0.079***	
		(-4.72)	
Del. Mortgage × Del. Auto Loan × Amt(Auto) | Bwr(Mortgage)			0.054***
			(3.88)
Del. Mortgage × Del. Credit Card Loan × Amt(Card) | Bwr(Mortgage)			-0.171***
			(-8.98)
Del. Mortgage × Del. Student Loan × Amt(Student) | Bwr(Mortgage)			-0.050***
			(-5.03)
Amt(Mortgage) | Bwr(Mortgage)			0.109***
			(6.87)
Floater	0.964***	0.870***	0.859***
	(15.24)	(14.76)	(14.28)
Subordination	-1.477***	-1.641***	-1.454***
	(-9.08)	(-9.65)	(-8.73)
WAL	-0.022***	-0.004	-0.003
	(-4.47)	(-0.64)	(-0.50)
Issuer Share	-1.561**	0.021	-0.563
	(-2.41)	(0.02)	(-0.55)
Principal	-0.137***	-0.123***	-0.121***
	(-9.14)	(-8.38)	(-8.28)
QE	-0.007***	-0.004***	-0.002*
	(-4.57)	(-2.84)	(-1.70)
GSE	0.001**	-0.001	0.000
	(2.08)	(-1.59)	(0.58)
Industrial Production	-0.050***	-0.029	-0.009
	(-2.85)	(-1.50)	(-0.45)
Case Shiller	-0.221***	-0.276***	-0.254***
	(-6.43)	(-7.08)	(-7.50)
Income	0.007*	-0.003	-0.007
	(1.77)	(-0.65)	(-1.53)
Unemployment	0.287***	0.161***	0.091***
	(9.60)	(4.48)	(2.66)
CPI	-0.468***	-0.562***	-0.808***
	(-6.96)	(-7.06)	(-11.88)
Rate	-0.123***	-0.119***	-0.150***
	(-8.40)	(-5.33)	(-8.99)
Wealth	-0.023***	-0.009	-0.010
	(-4.32)	(-1.21)	(-1.43)
Average Wealth	-0.007	0.025***	-0.007
	(-1.32)	(2.59)	(-0.61)
Constant	2.926***	-2.005***	-4.573***
	(5.45)	(-3.17)	(-6.24)
Issuer FE	yes	yes	yes
Rating FE	yes	yes	yes
Observations	36,060	31,564	31,564
Adjusted R^2	0.088	0.076	0.077

Table 7 continues on the next page.

Table 7 continued.

	Spread (1)	Spread (2)	Spread (3)
Panel B: The Pricing of Auto ABS and the Pecking Order			
Del. Auto Loan	0.481***	2.194***	1.479***
	(13.95)	(20.96)	(14.84)
Del. Auto Loan × Del. Mortgage		0.020*	
		(1.78)	
Del. Auto Loan × Del. Credit Card Loan		-0.092***	
		(-11.35)	
Del. Auto Loan × Del. Student Loan		-0.082***	
		(-11.20)	
Del. Auto Loan × Del. Mortgage × Amt(Mortgage) | Bwr(Auto)			0.002***
			(3.52)
Del. Auto Loan × Del. Credit Card Loan × Amt(Credit Card) | Bwr(Auto)			-0.106***
			(-7.65)
Del. Auto Loan × Del. Student Loan × Amt(Student) | Bwr(Auto)			-0.032***
			(-10.84)
Amt(Auto) | Bwr(Auto)			0.040***
			(7.38)
Observations	7,921	7,540	7,540
Adjusted R^2	0.744	0.759	0.752
Panel C: The Pricing of Credit Card ABS and the Pecking Order			
Del. Credit Card Loan	0.148***	0.019	0.041
	(4.85)	(0.28)	(0.49)
Del. Credit Card Loan × Del. Mortgage		0.042***	
		(3.26)	
Del. Credit Card Loan × Del. Auto Loan		0.030	
		(0.82)	
Del. Credit Card Loan × Del. Student Loan		-0.036***	
		(-4.33)	
Del. Credit Card Loan × Del. Mortgage × Amt(Mortgage) | Bwr(Credit Card)			0.003***
			(3.33)
Del. Credit Card Loan × Del. Auto Loan × Amt(Auto) | Bwr(Credit Card)			-0.020
			(-0.55)
Del. Credit Card Loan × Del. Student Loan × Amt(Student) | Bwr(Credit Card)			-0.004
			(-1.21)
Amt(Credit Card) | Bwr(Credit Card)			-0.972***
			(-3.02)
Observations	1,214	1,068	1,068
Adjusted R^2	0.686	0.717	0.717
Panel D: The Pricing of Student ABS and the Pecking Order			
Del. Student Loan	0.111***	0.091***	0.015
	(11.20)	(3.41)	(0.45)
Del. Student Loan × Del. Auto Loan		0.030**	
		(2.02)	
Del. Student Loan × Del. Credit Card		-0.021***	
		(-4.91)	
Del. Student Loan × Del. Mortgage		0.030***	
		(6.12)	
Del. Student Loan × Del. Auto Loan × Amt(Auto) | Bwr(Student)			0.038***
			(4.24)
Del. Student Loan × Del. Credit Card × Amt(Credit Card) | Bwr(Student)			-0.036***
			(-6.46)
Del. Student Loan × Del. Mortgage × Amt(Mortgage) | Bwr(Student)			0.003***
			(6.17)
Amt(Student) | Bwr(Student)			0.080
			(0.83)
Observations	1,396	1,396	1,396
Adjusted R^2	0.549	0.573	0.582

Table 8: The Pricing of ABS and the Pecking Order - Average Marginal Effects

This table shows the average marginal effects of households' delinquency preferences for model specification (3) shown in Tables 7. t-statistics are in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Average Marginal Effect			
	RMBS	Auto ABS	Credit Card ABS	Student ABS
	(1)	(2)	(3)	(4)
Del. Mortgage	0.781***	0.080***	0.228**	0.242***
	(9.48)	(3.89)	(3.16)	(6.17)
Del. Auto Loan	0.221***	0.968***	-0.137	0.320***
	(3.88)	(15.45)	(-0.53)	(4.24)
Del. Credit Card Loan	0.174***			
	(3.88)			
Del. Student Loan	-0.037***	-0.072***	-0.017	0.037
	(-5.03)	(-9.42)	(-1.25)	(1.11)
Amt(Auto) | Bwr(Mortgage) Auto Amount|Mortgage	0.174***			
	(3.88)			
Amt(Credit Card) | Bwr(Mortgage) Card Amount|Mortgage	-1.702***			
	(-8.98)			
Amt(Student) | Bwr(Mortgage)	-0.583***			
	(-5.03)			
Amt(Mortgage) | Bwr(Auto)		0.011***		
		(3.89)		
Amt(Credit Card) | Bwr(Auto)		-1.189***		
		(-7.34)		
Amt(Student) | Bwr(Auto)		-0.559***		
		(-9.42)		
Amt(Mortgage) | Bwr(Credit Card)			0.047**	
			(3.16)	
Amt(Auto) | Bwr(Credit Card)			-0.262	
			(-0.53)	
Amt(Student) | Bwr(Credit Card)			-0.170	
			(-1.25)	
Amt(Auto) | Bwr(Student)				0.606***
				(4.24)
Amt(Credit Card) | Bwr(Student)				-1.652***
				(-6.46)
Amt(Mortgage) | Bwr(Student)				0.049***
				(6.17)
Observations	31,564	7,540	1,068	1,396

Table 9: Rating Migration of RMBS and the Pecking Order

This table contains Logit models to examine the impact of households' delinquency decision on the rating migration probability of RMBS. *Del.* stands for new seriously delinquent balances (in %) for mortgages, as well as credit card and auto loans for the sample period 2003 to 2021 and for student loans for the sample period 2004 to 2021. The data contains the mean outstanding mortgage amount ($Amt(Mortgage) \mid Bwr(Mortgage)$) of held loans and the conditional mean of other loans if the household holds the respective loan ($Amt(m) \mid Bwr(Mortgage)$). $Floater$ is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. WAL denotes the tranche's weighted average life in years. $Issuer\ Share$ is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Financial and macroeconomic control variables are those listed in Table 4.The model specifications include issuer and rating fixed effects. The estimates are based on a downgrade within 36 months after the issuance of the tranche. *t*-statistics are in parentheses. We use non-parametric bootstrapped standard errors on 10,000 resampling runs with replacement. ***, **, * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Down RMBS	Down RMBS	Down RMBS
	(1)	(2)	(3)
Del. Mortgage	0.720***	-6.386***	-2.165***
	(3.68)	(-5.49)	(-3.18)
Del. Mortgage × Del. Auto Loan		1.197***	
		(2.67)	
Del. Mortgage × Del. Credit Card		-0.015	
		(-0.16)	
Del. Mortgage × Del. Student Loan		0.298***	
		(4.00)	
Del. Mortgage × Del. Auto Loan × Amt(Auto) | Bwr(Mortgage)			0.047
			(0.95)
Del. Mortgage × Del. Credit Card Loan × Amt(Card) | Bwr(Mortgage)			0.156**
			(-2.13)
Del. Mortgage × Del. Student Loan × Amt(Student) | Bwr(Mortgage)			0.187***
			(-3.78)
Amt(Mortgage) | Bwr(Mortgage)			-0.006
			(-0.10)
Floater	0.035	0.043	0.047
	(0.45)	(-0.62)	(-0.67)
Subordination	-0.555	-0.65	-0.781
	(-1.14)	(-1.38)	(-1.63)
WAL	0.014	0.017*	0.017
	(1.4)	-1.69	-1.63
Issuer Share	19.331***	24.180***	24.050***
	(4.48)	(6.21)	(6.09)
Principal	-0.076***	-0.074***	-0.075***
	(-4.98)	(-4.99)	(-5.10)
QE	-0.067**	-0.104***	-0.052**
	(-2.22)	(-4.76)	(-2.55)
GSE	0.022***	0.035***	0.031***
	(8.44)	(9.61)	(7.41)
Industrial Production	-0.231***	-0.244***	-0.240***
	(-3.71)	(-3.91)	(-3.96)
Case Shiller	0.570***	0.503***	0.401***
	(3.22)	(3.17)	(2.63)
Income	0.275***	0.298***	0.228***
	(3.22)	(3.7)	(3.43)
Unemployment	1.400***	1.866***	1.110***
	(3.92)	(6.03)	(4.51)
CPI	2.002***	1.682***	2.361***
	(-9.91)	(-5.47)	(-10.71)
Rate	2.622***	2.223***	2.102***
	(-15.93)	(-13.6)	(-16.39)
Wealth	-0.086***	-0.091***	-0.081***
	(-3.08)	(-3.35)	(-2.88)
Average Wealth	-0.133*	-0.289***	-0.200***
	(-1.74)	(-4.03)	(-2.59)
Issuer FE	yes	yes	yes
Rating FE	yes	yes	yes
Observations	27,330	23,375	23,375
Pseudo R^2	0.765	0.743	0.743

Table 10: Rating Migration of RMBS and the Pecking Order - Average Marginal Effects

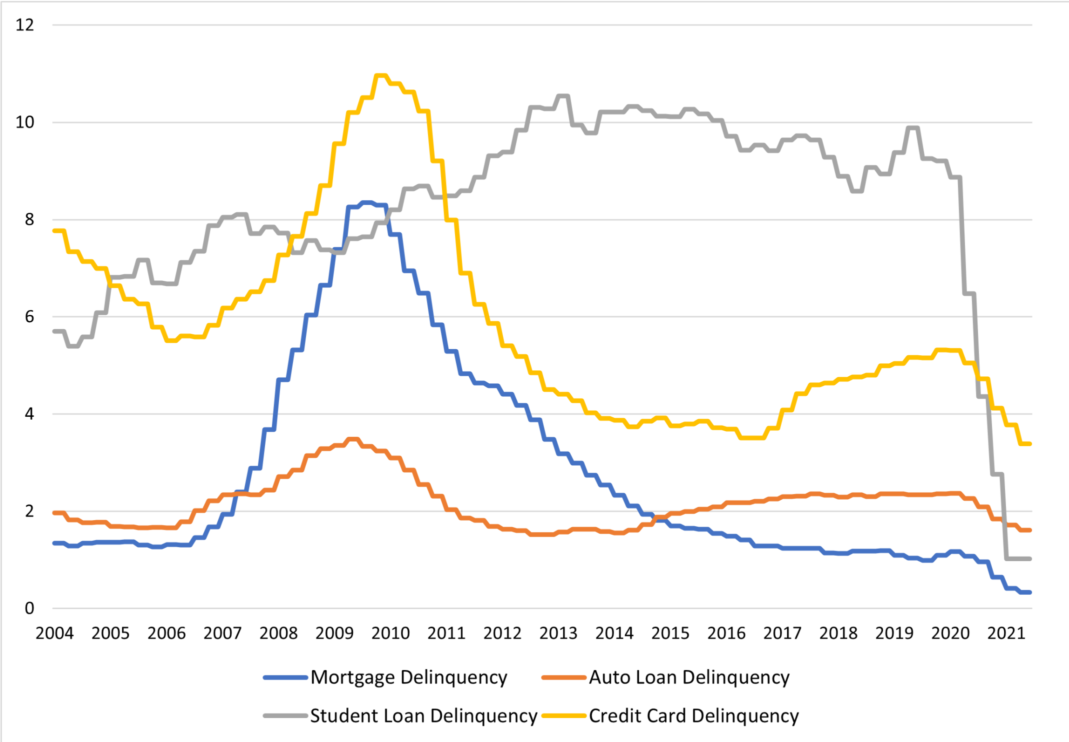
This table shows the average marginal effects of households' delinquency preferences for model specification (3) shown in Table 9. *Del.* stands for new seriously delinquent balances (in %) for mortgages, as well as credit card, auto, and student loans for the time period 2004 to 2021. t-statistics are in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	RMBS
Del. Mortgage	-0.043**
	(-2.11)
Del. Auto Loan	0.010
	(0.95)
Auto Amount|Mortgage	0.007
	(0.95)
Del. Credit Card	0.007**
	(2.13)
Card Amount|Mortgage	0.070**
	(2.12)
Del. Student Loan	0.006***
	(3.74)
Student Amount|Mortgage	0.104***
	(3.76)
Amt(Mortgage) | Bwr(Mortgage)	-0.000
	(-0.10)
Observations	23,375

Figures

Figure 1: Households' Delinquency Decision Making

This figure provides the monthly time series of the new seriously delinquent balances by loan type in percent for the years 2004 to 2021. The data is provided by the Federal Reserve Bank of New York.



Internet Appendix for

The Pricing of Asset-Backed Securities and Households' Pecking Order of Debt

Abstract

This paper studies the role of households' pecking order of debt in the pricing and rating migration of U.S. consumer debt asset-backed securities (ABS). Our empirical results show that the household's delinquency on mortgage and auto loan increases spreads of ABS using these loan types as collateral. Increasing delinquency on credit card and student loans often lower spreads of ABS with other collateral. We argue that delinquencies on these types of loans in a household's loan portfolio provide liquidity to other loans. In contrast, rising delinquencies on mortgages, the first to be repaid in the pecking order, are an indicator of a severe shock spilling over to other loan types, triggering a simultaneous increase in ABS spreads. Furthermore, we find for residential mortgage-backed securities (RMBS) a lower probability of future rating downgrades in times of high mortgage delinquency. Thus, ratings are adjusted according to changes in the business cycle.

JEL Classification: G12, G24.
Keywords: Asset-Backed Securities (ABS); Asset Pricing; Credit Risk; Household Finance; Pecking Order.

Table A.1: The Pricing of Auto ABS and the Pecking Order

This table shows OLS regressions of the *Spread* of privately issued Auto ABS tranches on households' delinquency preferences (Ω). *Del.* stands for new seriously delinquent balances (in %) for mortgages, as well as credit card and auto loans for the time period 2003 to 2021 and for student loans for the sample period 2004 to 2021. The data contains the mean outstanding mortgage amount ($Amt(Auto) \mid Bwr(Auto)$) of held loans and the conditional mean of other loans if the household holds the respective loan ($Amt(m) \mid Bwr(Auto)$). *Floater* is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. WAL denotes the tranche's weighted average life in years. $Issuer\ Share$ is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Financial and macroeconomic control variables are those listed in Table 4. The model specifications include *issuer and rating fixed effects.* t-statistics are in parentheses. We use non-parametric bootstrapped standard errors on 10,000 resampling runs with replacement. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Spread (1)	Spread (2)	Spread (3)
Del. Auto Loan	0.481***	2.194***	1.479***
	(13.95)	(20.96)	(14.84)
Del. Auto Loan × Del. Mortgage		0.020*	
		(1.78)	
Del. Auto Loan × Del. Credit Card Loan		-0.092***	
		(-11.35)	
Del. Auto Loan × Del. Student Loan		-0.082***	
		(-11.20)	
Del. Auto Loan × Del. Mortgage × Amt(Mortgage) | Bwr(Auto)			0.002***
			(3.52)
Del. Auto Loan × Del. Credit Card Loan × Amt(Credit Card) | Bwr(Auto)			-0.106***
			(-7.65)
Del. Auto Loan × Del. Student Loan × Amt(Student) | Bwr(Auto)			-0.032***
			(-10.84)
Amt(Auto) | Bwr(Auto)			0.040***
			(7.38)
Floater	-0.187***	-0.215***	-0.166***
	(-7.84)	(-7.87)	(-7.09)
Subordination	-0.258***	-0.416***	-0.343***
	(-4.13)	(-6.73)	(-5.75)
WAL	0.024**	0.028**	0.027**
	(2.19)	(2.52)	(2.43)
Issuer Share	-4.093***	-4.658***	-3.410***
	(-7.11)	(-6.97)	(-5.26)
Principal	-0.005	-0.002	-0.006
	(-1.22)	(-0.62)	(-1.38)
Industrial Production	-0.034***	-0.018	-0.013
	(-2.81)	(-1.24)	(-0.82)
Case Shiller	-0.099***	-0.067***	-0.089***
	(-5.29)	(-3.19)	(-4.89)
Income	0.011***	-0.001	0.004
	(4.24)	(-0.35)	(1.40)
Unemployment	0.231***	0.184***	0.185***
	(26.72)	(10.61)	(11.26)
CPI	0.704***	0.527***	0.691***
	(21.32)	(14.66)	(17.87)
Rate	-0.108***	-0.047***	-0.135***
	(-11.15)	(-4.03)	(-11.45)
Wealth	-0.020***	-0.016***	-0.020***
	(-6.91)	(-6.80)	(-7.39)
Average Wealth	-0.024***	-0.054***	-0.032***
	(-21.72)	(-16.08)	(-17.00)
Constant	1.284***	1.291***	0.810***
	(3.51)	(5.73)	(2.87)
Issuer FE	yes	yes	yes
Rating FE	yes	yes	yes
Observations	7,921	7,540	7,540
Adjusted R^2	0.744	0.759	0.752

Table A.2: The Pricing of Credit Card ABS and the Pecking Order

This table shows OLS regressions of the *Spread* of privately issued credit card ABS tranches on households' delinquency preferences (Ω). *Del.* stands for new seriously delinquent balances for mortgages (in %), as well as credit card and auto loans for the sample period 2003 to 2021 and for student loans for the sample period 2004 to 2021. The data contains the mean outstanding credit card amount ($Amt(Credit\ Card) \mid Bwr(Credit\ Card)$) of held loans and the conditional mean of other loans if the household holds the respective loan ($Amt(m) \mid Bwr(Credit\ Card)$). *Floater* is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. WAL denotes the tranche's weighted average life in years. $Issuer\ Share$ is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Financial and macroeconomic control variables are those listed in Table 4. The model specifications include *issuer and rating fixed effects*. t-statistics are in parentheses. We use non-parametric bootstrapped standard errors on 10,000 resampling runs with replacement. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Spread (1)	Spread (2)	Spread (3)
Del. Credit Card Loan	0.148***	0.019	0.041
	(4.85)	(0.28)	(0.49)
Del. Credit Card Loan × Del. Mortgage		0.042***	
		(3.26)	
Del. Credit Card Loan × Del. Auto Loan		0.030	
		(0.82)	
Del. Credit Card Loan × Del. Student Loan		-0.036***	
		(-4.33)	
Del. Credit Card Loan × Del. Mortgage × Amt(Mortgage) | Bwr(Credit Card)			0.003***
			(3.33)
Del. Credit Card Loan × Del. Auto Loan × Amt(Auto) | Bwr(Credit Card)			-0.020
			(-0.55)
Del. Credit Card Loan × Del. Student Loan × Amt(Student) | Bwr(Credit Card)			-0.004
			(-1.21)
Amt(Credit Card) | Bwr(Credit Card)			-0.972***
			(-3.02)
Floater	-0.641***	-0.573***	-0.561***
	(-8.45)	(-8.67)	(-7.84)
Subordination	-0.103	-0.179	-0.144
	(-0.29)	(-0.44)	(-0.37)
WAL	0.010	0.034***	0.036***
	(0.94)	(2.68)	(2.74)
Issuer Share	-0.574	-2.165**	-2.394**
	(-0.60)	(-2.12)	(-2.18)
Principal	0.008	-0.002	-0.001
	(1.36)	(-0.21)	(-0.13)
Industrial Production	-0.509***	-0.491***	-0.493***
	(-5.37)	(-4.97)	(-5.24)
Case Shiller	-0.167***	-0.109**	-0.143***
	(-3.47)	(-2.06)	(-2.68)
Income	0.083*	0.063	0.076
	(1.87)	(1.21)	(1.43)
Unemployment	0.090*	-0.136	-0.100
	(1.80)	(-1.55)	(-1.32)
CPI	0.408***	0.196*	0.343***
	(3.76)	(1.71)	(2.95)
Rate	-0.147***	-0.084**	-0.128***
	(-6.16)	(-2.55)	(-4.08)
Wealth	-0.036***	-0.002	-0.009
	(-4.47)	(-0.22)	(-0.91)
Average Wealth	-0.026***	-0.039***	-0.018**
	(-3.05)	(-3.70)	(-2.13)
Constant	1.136	4.833***	4.034***
	(0.91)	(3.78)	(3.28)
Issuer FE	yes	yes	yes
Rating FE	yes	yes	yes
Observations	1214	1068	1068
Adjusted R^2	0.686	0.717	0.717

Table A.3: The Pricing of Student ABS and the Pecking Order

This table shows OLS regressions of the *Spread* of privately issued student ABS tranches on households' delinquency preferences (Ω). *Del.* stands for new seriously delinquent balances (in %) for mortgages, as well as credit card and auto loans for the sample period 2003 to 2021 and for student loans for the sample period 2004 to 2021. The data contains the mean outstanding student loan amount ($Amt(Student) \mid Bwr(Student)$) of held loans and the conditional mean of other loans if the household holds the respective loan ($Amt(m) \mid Bwr(Student)$). *Floater* is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. WAL denotes the tranche's weighted average life in years. $Issuer\ Share$ is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Financial and macroeconomic control variables are those listed in Table 4. The model specifications include *issuer and rating fixed effects.* t-statistics are in parentheses. We use non-parametric bootstrapped standard errors on 10,000 resampling runs with replacement. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Spread (1)	Spread (2)	Spread (3)
Del. Student Loan	0.111***	0.091***	0.015
	(11.20)	(3.41)	(0.45)
Del. Student Loan × Del. Auto Loan		0.030**	
		(2.02)	
Del. Student Loan × Del. Credit Card		-0.021***	
		(-4.91)	
Del. Student Loan × Del. Mortgage		0.030***	
		(6.12)	
Del. Student Loan × Del. Auto Loan × Amt(Auto) | Bwr(Student)			0.038***
			(4.24)
Del. Student Loan × Del. Credit Card × Amt(Credit Card) | Bwr(Student)			-0.036***
			(-6.46)
Del. Student Loan × Del. Mortgage × Amt(Mortgage) | Bwr(Student)			0.003***
			(6.17)
Amt(Student) | Bwr(Student)			0.080
			(0.83)
Floater	-0.253***	-0.160***	-0.144**
	(-3.65)	(-4.07)	(-2.19)
Subordination	0.065***	-0.119	-0.369**
	(4.16)	(-1.13)	(-2.55)
WAL	0.025***	0.032***	0.031***
	(2.77)	(3.60)	(6.57)
Issuer Share	7.483***	7.207***	7.002***
	(4.48)	(3.30)	(5.12)
Principal	0.001	-0.006	-0.006
	(0.20)	(-0.40)	(-0.84)
Industrial Production	-0.155***	-0.134***	-0.130***
	(-12.09)	(-3.54)	(-5.32)
Case Shiller	-0.197***	-0.083*	-0.077**
	(-8.84)	(-1.72)	(-2.15)
Income	0.028***	0.022***	0.019*
	(5.76)	(6.48)	(1.73)
Unemployment	0.246***	0.163***	0.157***
	(16.28)	(4.39)	(5.72)
CPI	0.306***	0.100**	0.172***
	(11.33)	(2.09)	(2.65)
Rate	-0.175***	-0.122***	-0.078***
	(-34.71)	(-5.42)	(-2.81)
Wealth	-0.024***	-0.012	-0.014**
	(-3.42)	(-1.58)	(-2.47)
Average Wealth	0.018***	0.034***	0.020*
Constant	-0.608***	-0.380	0.208
	(-3.74)	(-0.82)	(0.36)
Issuer FE	yes	yes	yes
Rating FE	yes	yes	yes
Observations	1,396	1,396	1,396
Adjusted R^2	0.549	0.573	0.582

Table A.4: The Pricing of RMBS and the Pecking Order (Robustness Checks)

This table shows OLS regressions of the *Spread* of privately issued RMBS tranches on households' delinquency preferences (Ω). The model specifications are similar to basic model, however the macroeconomic variables are lagged by one month. *Del.* stands for new seriously delinquent balances (in %) for mortgages, as well as credit card and auto loans for the sample period 2003 to 2021 and for student loans for the sample period 2004 to 2021. The data contains the mean outstanding mortgage amount ($Amt(Mortgage)$ $\mid Bwr(Mortgage)$) of held loans and the conditional mean of other loans if the household holds the respective loan ($Amt(m) \mid Bwr(Mortgage)$). *Floater* is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. WAL denotes the tranche's weighted average life in years. *Issuer Share* is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Financial and macroeconomic control variables are those listed in Table 4. The model specifications include *issuer and rating fixed effects*. *t*-statistics are in parentheses. We use non-parametric bootstrapped standard errors on 10,000 resampling runs with replacement. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Spread (1)	Spread (2)	Spread (3)
Del. Mortgage	0.354***	1.734***	1.479***
	(8.50)	(6.32)	(8.90)
Del. Mortgage × Del. Auto Loan		-0.070	
		(-0.95)	
Del. Mortgage × Del. Credit Card Loan		-0.072***	
		(-4.57)	
Del. Mortgage × Del. Student Loan		-0.066***	
		(-3.79)	
Del. Mortgage × Del. Auto Loan × Amt(Auto) | Bwr(Mortgage)			0.053***
			(4.74)
Del. Mortgage × Del. Credit Card Loan × Amt(Card) | Bwr(Mortgage)			-0.192***
			(-9.87)
Del. Mortgage × Del. Student Loan × Amt(Student) | Bwr(Mortgage)			-0.046***
			(-5.03)
Amt(Mortgage) | Bwr(Mortgage)			0.133***
			(8.45)
Floater	0.958***	0.868***	0.860***
	(16.89)	(13.86)	(14.37)
Subordination	-1.517***	-1.654***	-1.477***
	(-9.35)	(-10.10)	(-8.95)
WAL	-0.021***	-0.003	-0.002
	(-4.24)	(-0.60)	(-0.35)
Issuer Share	-2.547***	-0.147	-0.962
	(-3.87)	(-0.15)	(-1.00)
Principal	-0.135***	-0.123***	-0.120***
	(-9.09)	(-8.34)	(-8.42)
QE	-0.000***	-0.000***	-0.000**
	(-6.06)	(-3.99)	(-2.36)
GSE	0.000***	0.000	0.000
	(3.50)	(0.83)	(0.59)
Industrial Production	-0.026	0.020	0.043**
	(-1.43)	(0.99)	(2.33)
Case Shiller	-0.141***	-0.159***	-0.167***
	(-4.16)	(-4.39)	(-5.08)
Income	-0.001	-0.013***	-0.022***
	(-0.32)	(-2.98)	(-4.84)
Unemployment	0.273***	0.151***	0.048
	(9.13)	(4.07)	(1.32)
CPI	-0.439***	-0.574***	-0.831***
	(-7.35)	(-7.59)	(-11.95)
Rate	-0.097***	-0.097***	-0.131***
	(-6.73)	(-4.62)	(-7.86)
Wealth	-0.018***	-0.013***	-0.008
	(-4.02)	(-2.76)	(-1.45)
Average Wealth	-0.005	0.004	-0.005
	(-0.78)	(0.57)	(-0.62)
Constant	2.627***	-1.447**	-5.530***
	(4.54)	(-2.51)	(-9.05)
Issuer FE	yes	yes	yes
Rating FE	yes	yes	yes
Observations	35,714	31,541	31,541
Adjusted R^2	0.086	0.074	0.075

Table A.5: The Pricing of Auto ABS and the Pecking Order (Robustness Checks)

This table shows OLS regressions of the *Spread* of privately issued auto ABS tranches on households' delinquency preferences (Ω). The model specifications are similar to basic model, however the macroeconomic variables are lagged by one month. *Del.* stands for new seriously delinquent balances (in %) for mortgages, as well as credit card and auto loans for the sample period 2003 to 2021 and for student loans for the sample period 2004 to 2021. The data contains the mean outstanding auto loan amount ($Amt(Auto) \mid Bwr(Auto)$) of held loans and the conditional mean of other loans if the household holds the respective loan ($Amt(m) \mid Bwr(Auto)$). *Floater* is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. *WAL* denotes the tranche's weighted average life in years. *Issuer Share* is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Financial and macroeconomic control variables are those listed in Table 4. The model specifications include issuer and rating fixed effects. *t*-statistics are in parentheses. We use non-parametric bootstrapped standard errors on 10,000 resampling runs with replacement. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Spread (1)	Spread (2)	Spread (3)
Del. Auto Loan	0.439***	2.137***	1.335***
	(12.40)	(18.38)	(12.98)
Del. Auto Loan × Del. Mortgage		0.039***	
		(3.91)	
Del. Auto Loan × Del. Credit Card Loan		-0.099***	
		(-12.19)	
Del. Auto Loan × Del. Student Loan		-0.086***	
		(-12.54)	
Del. Auto Loan × Del. Mortgage × Amt(Mortgage) | Bwr(Auto)			0.004***
			(5.23)
Del. Auto Loan × Del. Credit Card Loan × Amt(Credit Card) | Bwr(Auto)			-0.117***
			(-7.50)
Del. Auto Loan × Del. Student Loan × Amt(Student) | Bwr(Auto)			-0.030***
			(-9.58)
Amt(Auto) | Bwr(Auto)			0.042***
			(6.74)
Floater	-0.199***	-0.232***	-0.178***
	(-9.07)	(-9.74)	(-7.95)
Subordination	-0.215***	-0.364***	-0.295***
	(-3.05)	(-5.46)	(-5.05)
WAL	0.021**	0.025**	0.023**
	(2.07)	(2.49)	(2.20)
Issuer Share	-4.220***	-5.008***	-4.065***
	(-6.66)	(-7.67)	(-5.63)
Principal	-0.009**	-0.008	-0.011***
	(-2.27)	(-1.56)	(-2.76)
Industrial Production	-0.121***	-0.110***	-0.112***
	(-8.42)	(-7.04)	(-7.03)
Case Shiller	-0.039**	-0.003	-0.041**
	(-2.12)	(-0.18)	(-2.07)
Income	0.019***	0.013***	0.014***
	(5.43)	(3.35)	(3.94)
Unemployment	0.183***	0.128***	0.138***
	(21.63)	(8.65)	(11.52)
CPI	0.617***	0.472***	0.640***
	(19.53)	(13.43)	(19.80)
Rate	-0.092***	-0.023**	-0.111***
	(-11.57)	(-2.00)	(-8.53)
Wealth	-0.028***	-0.024***	-0.021***
	(-8.55)	(-7.67)	(-6.48)
Average Wealth	-0.026***	-0.057***	-0.030***
	(-21.85)	(-16.63)	(-14.34)
Constant	1.754***	1.890***	1.301***
	(4.90)	(8.72)	(6.20)
Issuer FE	yes	yes	yes
Rating FE	yes	yes	yes
Observations	7,917	7,536	7,536
Adjusted R^2	0.738	0.756	0.748

Table A.6: The Pricing of Credit Card ABS and the Pecking Order (Robustness Checks)

This table shows OLS regressions of the *Spread* of privately issued credit card ABS tranches on households' delinquency preferences (Ω). The model specifications are similar to basic model, however the macroeconomic variables are lagged by one month. *Del.* stands for new seriously delinquent balances (in %) for mortgages, as well as credit card and auto loans for the sample period 2003 to 2021 and for student loans for the sample period 2004 to 2021. The data contains the mean outstanding credit card amount ($Amt(Credit\ Card) \mid Bwr(Credit\ Card)$) of held loans and the conditional mean of other loans if the household holds the respective loan ($Amt(m) \mid Bwr(Credit\ Card)$). *Floater* is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. *WAL* denotes the tranche's weighted average life in years. *Issuer Share* is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Financial and macroeconomic control variables are those listed in Table 4. The model specifications include *issuer and rating fixed effects*. *t*-statistics are in parentheses. We use non-parametric bootstrapped standard errors on 10,000 resampling runs with replacement. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Spread (1)	Spread (2)	Spread (3)
Del. Credit Card Loan	0.226***	0.361***	0.366***
	(4.43)	(3.22)	(3.27)
Del. Credit Card Loan × Del. Mortgage		0.096***	
		(5.75)	
Del. Credit Card Loan × Del. Auto Loan		-0.116**	
		(-2.37)	
Del. Credit Card Loan × Del. Student Loan		-0.040***	
		(-4.98)	
Del. Credit Card Loan × Del. Mortgage × Amt(Mortgage) | Bwr(Credit Card)			0.005***
			(5.57)
Del. Credit Card Loan × Del. Auto Loan × Amt(Auto) | Bwr(Credit Card)			-0.122***
			(-3.03)
Del. Credit Card Loan × Del. Student Loan × Amt(Student)			-0.003
			(-0.81)
Amt(Credit Card) | Bwr(Credit Card)			-0.810**
			(-2.24)
Floater	-0.610***	-0.546***	-0.544***
	(-8.55)	(-7.49)	(-7.43)
Subordination	-0.206	0.003	0.075
	(-0.56)	(0.01)	(0.18)
WAL	-0.009	0.022*	0.021
	(-0.69)	(1.72)	(1.52)
Issuer Share	-1.706*	-3.303***	-3.579***
	(-1.82)	(-3.04)	(-3.01)
Principal	0.005	-0.000	-0.001
	(0.75)	(-0.01)	(-0.21)
Industrial Production	-0.312***	-0.283***	-0.299***
	(-4.06)	(-3.86)	(-3.71)
Case Shiller	-0.219***	-0.278***	-0.350***
	(-3.30)	(-3.68)	(-4.27)
Income	-0.086***	-0.034	-0.029
	(-3.00)	(-1.10)	(-1.01)
Unemployment	-0.095	-0.539***	-0.394***
	(-1.14)	(-4.25)	(-4.22)
CPI	0.657***	0.808***	0.827***
	(5.07)	(5.48)	(5.25)
Rate	-0.171***	-0.236***	-0.257***
	(-5.97)	(-5.40)	(-6.39)
Wealth	-0.030**	0.039**	0.037**
	(-2.08)	(2.22)	(2.08)
Average Wealth	-0.056***	-0.048***	-0.022**
	(-3.47)	(-4.87)	(-2.33)
Constant	1.926*	5.758***	4.114***
	(1.72)	(4.95)	(3.62)
Issuer FE	yes	yes	yes
Rating FE	yes	yes	yes
Observations	1,214	1,068	1,068
Adjusted R^2	0.645	0.692	0.691

Table A.7: The Pricing of Student ABS and the Pecking Order (Robustness Checks)

This table shows OLS regressions of the *Spread* of privately issued student ABS tranches on households' delinquency preferences (Ω). The model specifications are similar to basic model, however the macroeconomic variables are lagged by one month. *Del.* stands for new seriously delinquent balances (in %) for mortgages, as well as credit card and auto loans for the time period 2003 to 2021 and for student loans for the sample period 2004 to 2021. The data contains the mean outstanding student loan amount ($Amt(Student) \mid Bwr(Student)$) of held loans and the conditional mean of other loans if the household holds the respective loan ($Amt(m) \mid Bwr(Student)$). *Floater* is a dummy variable that indicates whether the tranche is a floating tranche. *Subordination* provides the fraction of subordinated debt of a tranche. WAL denotes the tranche's weighted average life in years. *Issuer Share* is a variable that tracks the market share of an issuer in the previous year. *Prinicpal* is the offered amount in USD 100 mn. Financial and macroeconomic control variables are those listed in Table 4. The model specifications include issuer and rating fixed effects. t-statistics are in parentheses. We use non-parametric bootstrapped standard errors on 10,000 resampling runs with replacement. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Spread (1)	Spread (2)	Spread (3)
Del. Student Loan	0.140***	0.178***	0.018
	(9.09)	(7.63)	(0.66)
Del. Student Loan × Del. Auto Loan		0.003	
		(0.29)	
Del. Student Loan × Del. Credit Card		-0.022***	
		(-11.11)	
Del. Student Loan × Del. Mortgage		0.036***	
		(9.60)	
Del. Student Loan × Del. Auto Loan × Amt(Auto) | Bwr(Student)			0.029***
			(5.13)
Del. Student Loan × Del. Credit Card × Amt(Credit Card) | Bwr(Student)			-0.034***
			(-9.55)
Del. Student Loan × Del. Mortgage × Amt(Mortgage) | Bwr(Student)			0.002***
			(6.41)
Amt(Student) | Bwr(Student)			0.219*
			(1.85)
Floater	-0.256***	-0.154**	-0.133***
	(-4.02)	(-2.49)	(-3.68)
Subordination	0.065	-0.053	-0.403***
	(0.97)	(-0.42)	(-7.42)
WAL	0.025***	0.032***	0.032***
	(4.18)	(5.27)	(13.13)
Issuer Share	7.540***	7.655***	7.304***
	(45.13)	(4.27)	(2.71)
Principal	-0.002	-0.005	-0.007
	(-0.09)	(-0.62)	(-0.30)
Industrial Production	-0.076***	-0.016	-0.004
	(-5.61)	(-0.71)	(-0.17)
Case Shiller	-0.110	-0.022	0.008
	(-1.52)	(-0.84)	(0.17)
Income	0.018***	0.003	0.001
	(4.96)	(0.29)	(0.08)
Unemployment	0.223***	0.110***	0.104***
	(16.59)	(5.52)	(4.69)
CPI	0.297***	0.078	0.185***
	(2.86)	(1.10)	(4.94)
Rate	-0.183***	-0.166***	-0.078***
	(-8.11)	(-7.89)	(-3.40)
Wealth	-0.040***	-0.036***	-0.034***
	(-10.83)	(-6.22)	(-3.86)
Average Wealth	0.024***	0.048***	0.012
	(3.06)	(7.88)	(1.18)
Constant	-0.846	-0.566	0.253
	(-1.12)	(-1.28)	(0.34)
Issuer FE	yes	yes	yes
Rating FE	yes	yes	yes
Observations	1,394	1,394	1,394
Adjusted R^2	0.544	0.572	0.580

Table A.8: The Pricing of ABS and the Pecking Order - Average Marginal Effects (Robustness Checks)

This table shows the average marginal effects of households' delinquency preferences for model specification (3) shown in Tables A.4 to A.7. t-statistics are in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	Average Marginal Effect			
	RMBS	Auto ABS	Credit Card ABS	Student ABS
	(1)	(2)	(3)	(4)
Del. Mortgage	0.939***	0.125***	0.430***	0.226***
	(10.95)	(5.23)	(5.57)	(6.41)
Del. Auto Loan	0.220***	0.858***	-0.839**	0.245***
	(4.74)	(14.41)	(-3.03)	(5.13)
Del. Credit Card Loan	-0.184***	-0.132***	0.255***	-0.162***
	(-9.87)	(-7.50)	(3.87)	(-9.55)
Del. Student Loan	-0.034***	-0.068***	-0.012	0.022
	(-5.03)	(-9.58)	(-0.81)	(1.06)
Amt(Auto) | Bwr(Mortgage)	0.173***			
	(4.74)			
Amt(Credit Card) | Bwr(Mortgage)	-1.915***			
	(-9.87)			
Amt(Student) | Bwr(Mortgage)	-0.534***			
	(-5.03)			
Amt(Mortgage) | Bwr(Auto)		0.017***		
		(5.23)		
Amt(Credit Card) | Bwr(Auto)		-1.306***		
		(-7.50)		
Amt(Student) | Bwr(Auto)		-0.526***		
		(-9.58)		
Amt(Mortgage) | Bwr(Credit Card)			0.088***	
			(5.57)	
Amt(Auto) | Bwr(Credit Card)			-1.606**	
			(-3.03)	
Amt(Student) | Bwr(Credit Card)			-0.122	
			(-0.81)	
Amt(Auto) | Bwr(Student)				0.463***
				(5.13)
Amt(Credit Card) | Bwr(Student)				-1.566***
				(-9.55)
Amt(Mortgage) | Bwr(Student)				0.046***
				(6.41)
Observations	31,541	7,536	1,068	1,394