DISCUSSION PAPER SERIES

DP11993

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FINANCIAL ECONOMICS

ISSN 0265-8003

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Discussion Paper DP11993
Published 24 April 2017
Submitted 24 April 2017

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Abstract

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JEL Classification: G14, G23, G01

Keywords: Securitization; Securities lending; Informed trading

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Acknowledgements

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August 2016

Abstract

In illiquid markets, trading by informed investors can have limited predictive power, because trading volumes are low and may not be timely. In these conditions, changes in the lendable amounts of securities can act as a canary in a coalmine, and predict future performance when trading activity cannot. We test this argument on the market for structured finance products ("securitized bonds"). We find strong evidence that changes in amounts available for lending (lendable) predict future performance (delinquency and foreclosure rates). In contrast, we do not find any evidence of predictability from changes in the amounts on loan. While investor trades have comparable predictive power to changes in lendable amounts in general, lendable amounts are a better predictor in illiquid markets. Overall, these findings are consistent with the hypothesis that securities holders (lenders) possess material information in this segment.

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It's one thing to bet on red or black and know that you are betting on red or black. It's another to bet on a form of red and not to know it [Lewis (2010)].

Introduction

Trading by informed investors plays a crucial role in financial markets, as a source of information. This intuition is behind, for instance, arguments that there should be no restriction on insider trading (Leland (1992)), or that short sale restrictions can make market prices less efficient (Miller (1977)). Indeed, a large body of evidence supports the notion that trading by certain classes of market participants, e.g. corporate insiders (Seyhun (1992), Meulbroek (1992)), institutional investors (Baker, Litov, Wachter, and Wurgler (2010), Puckett and Yan (2011)), or short sellers (Saffi and Sigurdsson (2011), Boehmer and Wu (2013)), is informative.

As an increasing volume of financial securities is traded in over-the-counter, illiquid markets, however, actual trading activity can become less informative, for at least two reasons. First, it is harder to observe trading volumes in OTC markets. Second, and more important, although *some* investors may possess valuable information and be willing to trade on it, lack of transparency and uncertainty can make the security illiquid, so that trading cannot occur in the first place, and thus cannot be informative.

In this paper, we propose to overcome these difficulties by looking at an additional signal of the presence of informed investors in the market: the amount of a security available for lending. Securities lending involves the temporary transfer of a security from a lender to a borrower, typically against cash and/or securities collateral. The global securities lending market has grown tremendously since the early 2000s, with several trillions of dollars on loan and many more available for lending, and is now close in size to its pre-crisis peak in 2007 (Dive, Hodge, and Jones (2011)). Increasingly, securities lending is an important component of the business model, and a sizeable source of funding, for insurance companies (Foley-Fisher, Narajabad, and Verani (2015)) and investment advisors (Evans, Ferreira, and Prado (2016)).

Securities lenders are typically large institutional investors who hold in their portfolio a security, which they make available for lending, earning a fee in the event that the security is loaned. Suppose the investor comes into possession of negative information regarding the future value of a given security, and would like to liquidate her holdings of it. Before she can sell the security, she will have to reduce the amount available for lending. As a result, a drop

in the lendable amount indicates a future worsening in the security's performance. Importantly, the signal from the lendable amount should be informative even in the presence of a market freeze, when investors are not readily able to sell their holdings. We provide empirical evidence consistent with this mechanism.

To run this test, we focus on securities lending in the structured finance products (henceforth, "securitized bonds") segment, as a relatively clean setting to take our argument to the data. Securitized bonds are a market segment of first-order economic importance: according to the Securities Industry and Financial Markets Association (SIFMA), as of 2012 its outstanding value in the U.S. was more than $10 trillion, or 1.4 times the size of the corporate bond market.

In addition, the features of the structured finance segment mirror the conditions of limited trading volumes and high information asymmetry at the root of our test. First, trading volumes can be low and uninformative. Securitized bonds typically trade in over-the-counter, illiquid markets, where the information content of trading activity might be limited, and trading itself is prone to freezes. This was especially true, for instance, in the wake of the financial crisis of 2007-09, where trading volumes in this segment dried up (Getter, Jickling, Lamonte, and Murphy (2007), Gorton (2008), Manconi, Massa, and Yasuda (2012)).

Second, this is a segment where information asymmetry considerations are very relevant. In fact, a debate has waged in the literature on whether or not (some) investors possessed information about structured finance products prior to the recent crisis. According to the "investor naïveté" view, market participants were largely oblivious to the risk associated with holding these securities (Bolton, Frexias, and Shapiro (2012), Skreta and Veldkamp (2009)). In contrast, the "regulatory arbitrage" view suggests that at least some investors were aware of a mispricing of risk in securitized bonds, which they exploited, e.g. to profitably circumvent regulatory restrictions on their holdings (Acharya and Richardson (2009), Calomiris (2009), Efing (2016)).

Using a novel, comprehensive dataset on securitized bonds lending and borrowing, our central finding is a strong, statistically robust relationship between changes in the amount of securities made available for lending ("*lendable*") and the future performance of securitized bonds' underlying pool of loans. Like a canary in a coalmine, a drop in the amount of a given security available for lending heralds a worsening performance of the underlying deal loans. This predictability result is economically meaningful, and it is immediately visible in the data,

as illustrated in Figure 3. Securities experiencing the largest decline in the lendable amount exhibit a 15% increase in delinquency rates, and a 14% increase in foreclosures, in their underlying pool of loans. The simple intuition from Figure 3 is confirmed in more formal, regression-based tests. Further, it is robust to the inclusion of *deal* fixed effects, i.e. to comparing securities whose value depends on the same underlying pool of loans.

In contrast, we do not find any evidence of predictability associated with securities *borrowing*. This runs counter to the intuition from the literature on the market for borrowing shares, typically motivated by short-selling, which does appear to predict future stock returns (D'Avolio (2002), Cohen, Diether, and Malloy (2007), Engelberg, Reed, and Ringgenberg (2012)). It is consistent, however, with fixed income securities borrowing having other objectives than short selling, for instance borrowing cash via a reverse repo agreement (Asquith, Au, Covert, and Pathak (2013)), as well as with anecdotal accounts such as Lewis (2010), suggesting that investors who wanted to short structured finance products would typically resort to alternative instruments, e.g. such as credit default swaps.

We argue that the possible economic mechanism underlying the predictive power of lendable amounts is described by the *informed lenders hypothesis*. Under this hypothesis, the holders of securitized bonds generally have superior information – due e.g. to the relative opacity of this market, as well as to the fact that they are typically large, sophisticated institutional investors (Manconi, Massa, and Yasuda (2012)). Their information advantage allows them to forecast a worsening performance of the securities they lend, and react by either liquidating them outright, or just recalling them so that they are no longer available for lending and are thus more readily liquidated. This will generate a drop in the lendable amount in anticipation of a worsening performance.

A potential alternative explanation is that it is not the securities holders, but rather the brokers/intermediaries, who have superior predictive ability. This is also plausible, given that, compared to a single investor, the intermediary can observe a larger number of signals coming from the many investors with whom she trades, and may thus be able to extract more precise information signal. When the intermediary forecasts worsening performance for a given security, she will no longer be willing to accept it as collateral for lending in a repo agreement. This will also generate a drop in lendable amount in anticipation of a worsening performance.

Both hypotheses, thus, are consistent with our baseline finding. They have, however, very different implications for the structure of the market for securitized bonds, as well as for

policy and regulation. By refusing to accept securities of worsening quality as collateral, informed prime brokers can limit the spread of risk through the financial system, confining underperforming assets to their holders, as well as reducing rehypothecation risk (Kahn and Park (2015), Singh (2015)). In contrast, if information rests with the holders (lenders) of securities, adverse selection problems about the quality of securitized bonds will be exacerbated, reducing liquidity (Morris and Shin (2012), Pagano and Volpin (2012), Vanasco (2014)), and/or exacerbating the risk and impact of fire sales (Shleifer (2011)).

To distinguish between the informed lenders and informed intermediaries hypotheses, we compare and contrast the predictive power of changes in lendable amount and investor sales. Under the informed *intermediaries* hypothesis, only lendable amount should have predictive power; investor trades should instead be uninformative (or less informative) about future performance: lendable amounts change exclusively in response to the pledgeability of a security as collateral.

In contrast, under the informed *lenders* hypothesis, investor sales will subsume part of the predictive power of changes in lendable amount, because the lenders would like to liquidate their holdings. The relative predictive ability of lendable vis-à-vis sales will depend, in turn, on liquidity. Investors will be able to sell the more liquid bonds, such that their trades will soak up the predictive power of changes in lendable. In contrast, they will not be able to sell less liquid bonds, such that changes in lendable will retain their predictive power. We use coupon size as a proxy for the expected liquidity of a given security, with higher coupons associated, ceteris paribus, with lower liquidity. Therefore, changes in lendable amounts will have stronger predictive power for securities with high coupons, and trading for securities with low coupons.

Our results confirm this prediction. Indeed, we find in general that investor trades have predictive power for the future performance of securitized bonds, comparable to that of changes in lendable amount. However, their predictive power is limited to the set of securities with a lower coupon; for higher-coupons, only changes in lendable amount predict performance. Additional tests based on lending fees (omitted for brevity) fail to provide any support for the informed intermediaries hypothesis.

In a future draft of the paper, we plan to look at more direct proxies for liquidity, based on actual trading activity. We also plan to investigate the potential channels through which securities lenders acquire information. One possibility, which we are currently investigating

is affiliation to a financial conglomerate, e.g. one encompassing investment banks that underwrite securitized bonds.

Our paper makes three main contributions to the literature. First, it contributes to the Literature on information asymmetry and the role of informed traders in financial markets. The literature has focused on actual trading activity, such as insider traders (Seyhun (1992), Meulbroek (1992)), or the trades of short sellers (Cohen, Diether, and Malloy (2007), Saffi and Sigurdsson (2011)). But as we argued, trading activity can be an inadequate tool to establish the presence of informed investors, particularly in conditions of low liquidity when the informed investors themselves might be unable to trade on their information. We show that lendable amounts act as an additional, potentially cleaner signal, which in contrast to trading can be effective even in illiquid markets.

Second, it contributes to the recent literature on securities lending. While a large body of has studies the behavior and information content of securities borrowing and in particular short selling, much less is known about its counterpart, securities lending. A number of recent studies has started to fill this gap. Foley-Fisher, Narajabad, and Verani (2015) and Evans, Ferreira, and Prado (2016) show that securities lending has become an important source of funding for financial intermediaries such as insurance companies and investment advisors. Prado, Saffi, and Sturgess (2016) show ownership structure, through its impact on lendable amounts, can introduce limits to arbitrage and, consistent with the arguments of Miller (1977), have an impact on price informativeness. Because of its potential impact on firm-level and systemic risk, Adrian, Begalle, Copeland, and Martin (2013) advocate greater transparency and analysis of the securities lending market. We provide evidence of the informational role of the securities lending market, and in particular of changes in lendable amounts as a distress signal.

Third, it contributes to the literature on structured finance and securitization (Coval, Jurek, and Stafford (2009)). There is abundant evidence that, possibly due to incentives faced by their issuers (Pagano and Volpin (2012)), the structured finance market is characterized by great complexity and opacity (Celerier and Vallee (2014)), and even fraud regarding the quality of individual deals (Griffin and Maturana (2016), Piskorski, Seru, and Witking (2015)). Due to the central role these assets played in the financial crisis of 2007-08 (Brunnermeier (2008), Gorton (2008)), and the potential systemic risk associated with them (Manconi, Massa, and Yasuda (2012), Merrill, Nadauld, Stulz, and Sherlund (2013)), a key question in the literature is, what financial market participants possess material information regarding their

valuation. Rating agencies are an obvious candidate (Kempf (2015), Stanton and Wallace (2010)), but the market does not appear to rely exclusively on credit ratings (Adelino (2009), He, Qian, and Strahan (2014)). The literature is split between the "investor naïveté" view, suggesting that the vast majority of market participants was unaware of the risks associated with structured finance products, and the "regulatory arbitrage" view, which argues that at least a meaningful subset of investors was informed. We contribute to this literature by providing evidence consistent with the argument that the holders of securitized bonds, who make them available for lending, possess information about their future performance.

The remainder of the paper is articulated as follows. Section II describes the data sources and the main variables of interest used in the analysis. Section III reports our central finding, that securities lending predicts the performance of securitized bonds. Section IV considers two alternative economic mechanisms explaining the predictability result, based on the informed intermediaries and lenders hypotheses, and presents evidence more supportive of the latter. Section V concludes.

II Data

We merge data from a variety of sources: the CUSIP Master File, the Lipper eMAXX fixed income securities holdings database, Bloomberg Loan Performance database, and the DataExplorers securities lending database.

A. Some details on the securitized assets

We now briefly describe the structure of the securitized bonds in our sample. Each issue (henceforth, "deal") is based on a portfolio of underlying loans: mortgages, student loans, credit card debt, etc.

Figure 1A describes the breakdown of our sample securities by type of underlying loans; the underlying are classified according to information from the Bloomberg Loan Performance database. The largest group of deals consists of general Asset Backed Securities (ABS, 49% of the total), comprising ABS with underlying home loans ("Home"), credit card debt ("Cards"), Auto loans ("Auto"), and a residual category "Other". Along with these, the sample also comprises Collateralized Mortgage Obligations (CMO, 34%), Commercial Mortgage-Backed Securities (CMBS, 8%), government agency-backed securities (Agency, 7%), and a residual category for all other deals (Other, 2%).A given portfolio is then broken down

into a number of tranches, having a different seniority and, as a consequence, a different rating. Tranches with a lower seniority absorb any losses (loan defaults) first, and a given higher-seniority tranche does not take any losses until all tranches of lower seniority have been wiped out. In total, our sample contains 3,973 deals issued between January 2000 and June 2010, broken down into 9,180 tranches. As shown in Figure 1B, the majority of tranches in our sample have a AAA rating at issuance (67% based on S&P ratings, 67% based on Moody's ratings, and 62% based on Fitch ratings). This is consistent with the findings in the literature that institutional investors, whose holdings typically provide the bulk of securities in the lending market, as we discuss below, largely hold securitized assets with AAA rating due to regulatory constraints (Herring and Schuermann (2005), Manconi, Massa, and Yasuda (2012)). The remainder consists mostly of non-AAA, investment grade securities (30-35%), and only a tiny fraction of speculative grade securities (2-5%).

B. Securities lending and borrowing data

We obtain securitized bonds lending data from DataExplorers, a privately owned company that supplies financial benchmarking information to the securities lending industry and short-side intelligence to investment managers. DataExplorers collects data from custodians and prime brokers that lend and borrow securities, and is the leading provider of lending data world-wide. For each security, DataExplorers reports the lendable quantity (in $1,000 par amount value) and the total balance quantity (in $1,000 par amount value) at monthly frequency.[1]

The mechanics of lending and borrowing securitized bonds is similar to that of other fixed income securities (e.g. Asquith, Au, Covert, and Pathak (2013)). Investors typically borrow bonds through an intermediary such as a depository bank. Such banks act as custodians for the securities, and pay lenders (depositors) a fee in exchange for the right to lend them out. The security borrower must post collateral, corresponding to 102% of the market value of the borrowed bond. Loans are typically collateralized with cash or US Treasuries. In our sample period, cash collateral is about 94% of the amount on loan for the

[1] For a more recent subset of the data, this information is also available at the weekly frequency; and for an even smaller sub-sample, at the daily frequency. To maximize sample coverage, as well as to combine DataExplorers data with information e.g. from Lipper eMAXX, which comes at the quarterly frequency, we collapse these data to the monthly or quarterly frequency throughout the analysis.

average security, comparable to the 99% reported by Asquith, Au, Covert, and Pathak (2013) for the corporate bond market.

The security borrowing-lending transaction, thus, involves three parties: (i) a security borrower; (ii) the intermediary, depository bank; and (iii) the owner of the security. The security borrower pays a fee for the security loan, and receives a rebate rate in return for the use of the collateral she posts. The owner of the security, typically an institutional investor (Asquith, Pathak, and Ritter (2005)), receives a fee from the depository bank. The rebate rate may be larger than the fee paid by the security borrower, in which case the owner of the security effectively borrows the collateral (cash) from the security borrower, paying an interest equal to the rebate rate minus the security loan fee.

The DataExplorers database covers the entire market for lending fixed income securities in the U.S. Thus, we are able to evaluate the size of the securitized bonds lending market, and compare it to the markets for lending stocks and corporate bonds. Equity short sales (borrowing) transactions have been found to represent about 2.5% of NYSE and AMEX market cap (Asquith, Pathak, and Ritter (2005)) or about one third of share trading volume on NYSE and NASDAQ (Diether, Lee, and Werner (2002)). Asquith, Au, Covert, and Pathak (2013) report an average daily par value of corporate bonds shorted of $3.3 Bn, or 19% of all corporate bond trades. The average daily par value of securitized bonds on loan in our sample is $103 million. This is consistent with the impression among practitioners that the market for borrowing securitized bonds is smaller than those for stocks and corporate bonds. At the same time, the market appears economically non-negligible, accounting for 22% of the outstanding amount of the securities on loan on average, or utilization ratio of about 1%.[2]

C. Performance measures

From the Bloomberg Loan Performance Database, we obtain measures of the performance of the securitized bonds in our sample. During our sample period, securitized bonds are very thinly traded, and largely over the counter. Measures of the price of individual securities could in principle be obtained, but they are mostly based on matrix pricing: they are not market prices, and thus need not reflect the effective economic value of the security.

[2] Since there is no liquid market for securitized bonds, an estimate of the amount on loan as a fraction of daily trading volume is not available.

We thus turn to two measures of performance based on the value of the underlying portfolio of assets: the monthly (or quarterly) changes in *90-day delinquency* and *Foreclosure rate*.

The change in *90-day delinquency* and *Foreclosure rate* are computed at the deal level. The change in *90-day delinquency* rate refers to the monthly (or quarterly) change in the fraction of loans underlying a given deal that are more than 90 days delinquent. The change in *Foreclosure rate* refers to the monthly (or quarterly) change in the fraction of loans underlying a given deal that are in foreclosure. An increase in *90-day delinquency* or *Foreclosure rate*, thus, implies a worsening performance for the entire deal.

Compared to a more standard measure of performance such as market returns, the delinquency and foreclosure rates that we use have pros and cons. On the one hand, they are not based on market trades, and are not forward-looking, so they need not reflect the expectations of the marginal investor. This is not a problem, however, because the objective of our baseline tests is to predict ex post performance of the securities (and based on that determine which market participant(s) are informed). On the other hand, they are near-perfect measures of the quality of the underlying economic fundamentals of the security, unlike the secondary-market return on a stock or corporate bond, which can be at best a noisy proxy.

The average monthly change in *90-day delinquency rate* (*Foreclosure rate*) is 0.27% (0.12%, Table I), with a standard deviation of 1.21% (1.04%). Figure 2A describes the time series of these performance measures. Consistent with anecdotal accounts of this market, following a long period of virtually no foreclosures or delinquencies, the performance of securitized assets in our sample began to worsen on average in early 2007, reaching a peak in 2009. The worsening performance is more pronounced for smaller issues – the value-weighted averages in Figure 2A reach a peak around 3% (for both *90-day delinquency* and *Foreclosure rate*), while the equal-weighted averages around 7.5%.

Interestingly, however, there is a wide distribution around the averages, as shown in panel B. As of 2009, in the midst of the recent financial crisis, there are deals with delinquency rates as high as nearly 40% (95th percentile), as well as deals with no delinquencies at all (25th percentile). There is room, therefore, for informed market participants to predict the difference between securities associated with deals of such differing performance.

D. Identifying information and institutional holdings data

The CUSIP Master file contains identifying information, standardized descriptions, and additional data attributes for any corporate, municipal, and government security with a CUSIP code offered in North America. We complement these data with deal characteristics retrieved from the Bloomberg Loan Performance database: size (amount) of the issue, level of subordination, credit rating(s) at the time of the issue, number of ratings available on the issue, weighted-average life of the underlying loans, median FICO score, geographic concentration, as well as the percentage of collateral located in "troubled" states (He, Qian, and Strahan (2014)).

The Lipper eMAXX database contains details of corporate bonds and securitized bonds (mortgage- and asset-backed securities, collateralized debt, mortgage, or loan obligations, and their variants) holdings for nearly 20,000 U.S. and European insurance companies, U.S., Canadian, and European mutual funds, and leading U.S. public pension funds. It provides information on quarterly ownership of more than 50,000 fixed income issuers with over $7 trillion in total par amount, from 2000Q1 to 2008Q1. Holdings are recorded in units of $1,000 in par amount, not in market values. This allows us to accurately measure quarterly quantity changes (as opposed to market value changes) in holdings of individual bonds; we use changes in holdings as a measure of active trading on part of institutional securities holders.

E. Key securitized bonds lending and borrowing proxies

A unique feature of the DataExplorers database is that, for each security, it reports both the quantity that is on loan at a given point in time, as well as the quantity that is available for lending. In other words, it allows us to *directly* observe the demand and supply sides of the market. We are thus able to compute three key variables of interest, related to securitized bonds lending and borrowing.

The first one is *Lendable/Issue Amount*, computed for a given tranche as:

$$\frac{\text{Quantity available for lending}}{\text{Issue amount}} \tag{1}$$

The quantity available for lending is obtained from DataExplorers, while the issue amount comes from the Mergent FISD database. This variable measures the supply of the security available for lending at a given point in time.

The second one is *Lent/Issue Amount*, computed for a given tranche as:

$$\frac{\text{Quantity on loan}}{\text{Issue amount}} \tag{2}$$

The quantity on loan is obtained from DataExplorers, while the issue amount comes from the Mergent FISD database. This variable measures the demand for borrowing the security at a given point in time.

The third one is the *Utilization ratio*, computed for a given tranche as:

$$\frac{\text{Quantity on loan}}{\text{Quantity available for lending}} \tag{3}$$

This variable measures the excess demand for borrowing the security at a given point in time.

Throughout the analysis, we will focus on monthly or quarterly changes in *Lendable/Issue amount*, *Lent/Issue amount*, and *Utilization ratio*, and relate them to the future performance of individual securitized loans.

Table II relates security lending and borrowing to a number of security characteristics. We focus on characteristics that are likely to affect the demand and supply for securities loans: size at issuance, level of subordination, maturity, coupon, rating and rating uncertainty (proxied by an indicator for initial disagreement among different ratings), as well as creditworthiness of the underlying loans, proxied by median FICO score, loan-to-value ratio (LTV), percentage of adjustable-rate mortgage (ARM) loans, geographic concentration of collateral, in particular in "troubled" U.S. states especially exposed to the subprime crisis (He, Qian, and Strahan (2014)).

Specifications (1) and (2) in Table II indicate that, similar to the corporate bond market (Asquith, Au, Covert, and Pathak (2013)), securitized bonds are more likely borrowed when they are large. Unlike corporate bonds, however, securitized bonds borrowing is not driven by default risk – at least not insofar as it is captured by rating at issuance, FICO score, or LTV.

In contrast, specification (3) highlights that default risk, and in particular the creditworthiness of the underlying pool of loans, is much more important for the decision to make the securitized bonds available for lending. Securities with a higher median FICO score, less geographically concentrated underlying loans, and lower exposure to troubled states, are more likely available for lending.

This is consistent with the securities' lenders taking into account information about the quality of the underlying pool of assets in their lending decision. As in the equity market (Asquith, Pathak, and Ritter (2005)), lenders are typically large, institutional investors. That such sophisticated market participants should have access to superior information about collateral quality, or be better able to interpret publicly available information, is perhaps not

surprising; it has, however, important implications for lending as a predictor of the performance of securitized assets, as we discuss in the next section.

III Predicting the Performance of Securitized Bonds

In this section, we present our central result. We show that decreases in the amounts of securitized bonds made available for lending predict worsening performance of the securities, proxied by *90-day delinquency* and *Foreclosure rate*. In contrast, we find no evidence that changes in securities *borrowing* predict performance. These results hold at the deal as well as at the tranche level; and in particular, they hold after controlling for deal fixed effects, i.e. fixing the securities' underlying economic fundamentals, except in terms of the exposure to default risk. We further show that the result is driven by decreases in the amount of securities made available for lending – i.e., increases in the amount of securities made available for lending do not predict an improving performance. We discuss two potential interpretations of these findings, pointing to two distinct economic mechanisms behind our results.

A. Predictability: the evidence

We start by relating changes in the amounts of securitized bonds made available for lending to securitized bonds performance, with a simple test akin to an event study. Each calendar month, we sort the deals in our sample into quintiles, based on the change in *Lendable/Issue amount* relative to the previous month. We then track the average performance of the deals in each quintile over the subsequent 6 months.

Figure 3 provides a visual description of the results, which indicate that changes in securities lending are a strong predictor of the subsequent performance of the underlying pool of loans. Deals in the bottom quintile, experiencing the largest decrease in *Lendable/Issue amount*, exhibit a 14.4% increase in *90-day delinquency rate*, and a 15.2% increase in *Foreclosure rate*, over the subsequent 6 months. In contrast, deals in the top quintile display a modest improvement in performance: a 2.4% drop in delinquency rates, and a 1.4% drop in foreclosures.

As a more formal test, we consider a baseline regression specification:

$$Perf_{it+1} = \alpha + \beta Lendable/Issue\ Amount_{it} + \gamma' x_{it} + \varepsilon_{it} \quad (4)$$

where $Perf_{it+1}$ denotes the monthly change in *90-day delinquency* or *Foreclosure rate* on deal i in month $t+1$. In a separate set of regressions, we also run (4) on tranche-level securities

lending data. *90-day delinquency* and *Foreclosure rates* are only available at the deal level. For a small number of deals, we could obtain directly from Bloomberg information on the losses on individual tranches. On this set, most of the results we describe below are confirmed.

We also run separate regressions in which we focus on securities borrowing, as opposed to changes in the amounts of securitized bonds made available for lending, and thus *Lendable/Issue Amount* is replaced by *Lent/Issue Amount*. In all the specifications, x_{it} denotes a vector of deal characteristics: log issue amount, number of ratings available from different rating agencies, log weighted-average life, median FICO score of the underlying pool of loans (with an indicator if the information on FICO score is missing), geographic concentration of the underlying pool of loans, and the percentage of collateral located in "troubled" U.S. states (He, Qian, and Strahan (2014)). The control variables also include deal type and calendar month fixed effects.

Importantly, the richness and depth of our data, as well as the nature of the securitized assets we study, allow us to include *deal* fixed effects in our specifications. This means that, when running the tranche-level tests, we can compare securities that are, by construction, identical in terms of their underlying economic fundamentals – they are based on the very same set of underlying bonds. The only difference between different tranches is their holders' exposure to default risk, due to the different seniority levels. Thus, when we relate changes in in the amounts of each tranche made available for lending to changes in their performance, we can control for omitted/unobservable factors that could potentially confound our estimates and that should vary across *deal,* but for which we can control within deals. Table III reports the central findings of our paper: a drop in lending predicts a worsening performance. We find a strong, negative association between changes in *Lendable/Issue Amount* and next-month performance, measured by the change in *90-day delinquency* or *Foreclosure rate*.

The effects are also economically meaningful: a 1 percentage point decrease in *Lendable/Issue Amount* predicts an increase in *90-day delinquency* rate by 0.45 percentage points, and an increase in *Foreclosure rate* by 0.21 percentage points.[3] For the average bond in our sample, *Lendable/Issue Amount* is 21%, the *90-day delinquency rate* is 13%, and the *Foreclosure rate*

[3] These effects are estimated as follows. The coefficient on *Lendable/Issue amount* in Table IIIA, column (2), is –0.457; multiplying that by a 1 percentage point decrease, we obtain the 0.45 percentage point increase in *90-day delinquency rate*. Likewise, the coefficient in column (4) is –0.207; multiplying that by a 1 percentage point decrease, we obtain the 0.21 percentage point increase in *Foreclosure rate*. Economic effects are computed analogously throughout the paper.

is 5%. Thus, a decrease by about 5% of the mean *Lendable/Issue Amount* is associated with a 4% worsening performance, confirming the intuition of Figure 3 and suggesting that the effects implied by our estimates are indeed substantial.

They also hold across both deal- (panel A) and tranche-level (panel B) specifications, and are robust to the inclusion of the full set of control variables, as well as to controlling for deal fixed effects. In other words, the estimates of panel B imply that the predictability result obtains even when comparing securities that are by construction identical in terms of their underlying economic fundamentals, and only differ in their exposure to defaults due to the different seniority. These results suggest that changes in the amount of a given security available for lending predict its next-month performance.

On the other hand, the estimates reported in Table IV show that changes in the amount *lent* do not predict future performance. Across the various specifications, the coefficients on the change in *Lent/Issue Amount* are sometimes positive, sometimes negative, and always insignificantly different from zero.

This is consistent with the evidence of Asquith, Au, Covert, and Pathak (2013) that securities lending in the fixed income market is typically not used to speculate via a short position. Their evidence is based on the corporate bond market, but an even stronger case can be made for securitized bonds: just as corporate bonds, most of the trading in these securities takes place over the counter; however, compared to corporate bonds they are much more thinly traded, and information asymmetry and search costs are likely even more relevant. Thus, speculation is more likely to occur via other strategies, e.g. involving credit derivatives – consistent with popular accounts of the 2007-8 financial crisis such as Lewis (2010).

To conclude this section, we perform an additional test dissecting the predictability results reported in Table III. We re-run specification (4) on two sub-samples, corresponding to increases and decreases in *Lendable/Issue Amount*. The estimates are reported in Table V. They show that it is exclusively *negative* changes in the amount of securities lending that predict worsening performance (columns (2) and (4) of both panels A). The economic effects implied by these estimates are also larger: a 10 percentage points decrease in *Lendable/Issue Amount* is associated with an increase in *90-day delinquency rate* by over 10 percentage points, and an increase in *Foreclosure rate* by 6 percentage points. Increases in securities lending, in contrast, do not predict improvements in performance; in these specifications, the coefficients on the change in *Lendable/Issue Amount* is small and insignificant (columns (1) and (3)). The

implication of these estimates is that the predictor of securitized bonds performance that we have identified in Table III – *Lendable/Issue Amount* – is really a predictor of *worsening* performance.

To sum up, the evidence presented so far indicates that a decrease in the amounts of securitized bonds made available for lending is a significant predictor of (worsening) securitized assets performance. It predictive power is not subsumed by standard controls for security characteristics, and is even robust to the inclusion of deal fixed effects – i.e. to comparing securities that are by construction identical in terms of their economic fundamentals, with the exception of the differential exposure to default risk associated with different tranches.

It is worth noting that *Lendable/Issue Amount* is an indicator that can be measured in real time. This makes itat least in principle, a very useful indicator for policy makers as it can directly inform the decisions of market participants as well as regulators.

B. Interpretations

The interesting question is, why does lendable predict performance? At first glance, this is surprising, as there is no evidence in the literature that anything similar happens, for instance, in the equity market (Cohen, Diether, and Malloy (2010)) or in the corporate bond market (Asquith, Au, Covert, and Pathak (2013)). There are two possible explanations, each related to the unique features of the fixed income securities lending market.

The first possibility is that at least some of the securities holders have superior predictive ability regarding the performance of the pool of assets underlying the securities that they hold and make available for lending. This is plausible, given the general opacity of these securities, and the evidence that they are largely held by large, sophisticated institutional investors (Manconi, Massa, and Yasuda (2012)). Such specialized investors may have either access to superior information about the underlying loans, or greater ability to interpret public information (Engelberg, Reed, and Ringgenberg (2012)), which enable them to forecast a worsening future performance. Faced with this forecast, the investors choose to outright liquidate their holdings of the securities, or recall them, such that they are no longer available for lending and are thus more readily liquidated. This will generate a drop in lending in anticipation of a worsening performance.

The second possibility is that it is not the securities holders, but rather the intermediaries ("brokers"), who have superior predictive ability. This is also plausible, given e.g. the evidence that at least some institutional investors absorbed losses on their securitized assets holdings in the midst of the 2007-2008 crisis (Manconi, Massa, and Yasuda (2012), or the popular account given by Lewis (2010)), and the fact that, compared to individual investors, the broker can observe a larger number of signals coming from the many investors with which she trades, and may thus be able to extract more precise information. As a result, when the broker forecasts worsening performance for a given security, she will not be willing to accept it as collateral for lending. This will also generate a drop in lending in anticipation of a worsening performance, consistent with the evidence provided so far.

IV Informed Traders or Informed Intermediaries?

How to distinguish between the two interpretations of the evidence described above?

To the extent that the predictability result is due to superior information (or information processing ability) on part of the holders of securitized bonds, we can expect that not only changes in the amount available for lending, but also investor trades, will have predictive power towards future performance. This would be consistent with recent evidence that the trades of institutional investors contain information that predicts performance (e.g., Baker, Litov, Wachter, and Wurgler (2010), Puckett and Yan (2011)).

Furthermore, making securities available for lending and investor trades should differ, other things equal, along a crucial dimension: liquidity. Consider the position of a given investor who, having initially made her security available for lending, forecasts a worsening performance. The investor would want to recall the security, so that it is no longer lendable, and immediately sell it to avoid absorbing the loss deriving from the upcoming bad performance. In a liquid market, the sale occurs immediately. In an illiquid market, information asymmetry and search costs can prevent the sale from taking place in a timely manner. The implication is that, in a liquid market, investor sales should subsume the predictive power of changes in lendable. In an illiquid market, however, selling activity may fail to predict a worsening performance, so that changes in lendable retain their predictive power.

We take coupon rates as a proxy for liquidity, with higher coupon rates associated with lower liquidity (in a future draft of the paper, we plan to consider more direct proxies for

liquidity, based on actual trading activity). We thus preduct that lendable amounts will have greater predictive power for securities with a high coupon, while with a lower coupon its predictive power will be similar to, or potentially even lower than, investor sales. In contrast, the informed intermediaries hypothesis implies predictability exclusively in terms of lendable amounts, and it makes no prediction at all regarding the role of different coupons.

As a proxy for decreases in lendable amounts, we consider *Negative ΔLendable*, equal to the absolute value of the change in *Lendable/Issue Amount* if negative, and zero otherwise. As a proxy for investor trading activity we consider *Investor sales*, defined as the percentage of institutional investors in the Lipper eMAXX database who decrease their holdings of a given security at a given point in time. We then run a horse race, using *Lendable/Issue Amount* and *Investor sales* as alternative predictors for securitized bonds' performance, measured again as *90-day delinquency* and *Foreclosure rate*.

The results of the test are reported in Table VI. Panel A considers predictive regressions using *Lendable/Issue Amount* only, panel B using *Investor sales* only, and panel C combining both predictors. The results support the informed investors hypothesis. First, the evidence of panel B (and C) shows that investor sales have strong predictive power. The coefficient on *Investor sales* is positive and statistically significant, and a 1 percentage point increase in *Investor sales* predicts a 0.04 percentage points increase in *90-day delinquency*, and a 0.02 percentage points increase in *Foreclosure rate*. Similarly, and consistent with the results of Tables III and V, an increase *Negative ΔLendable* predicts worsening performance.

Second, the combined evidence of panels A, B, and C shows that the predictive power of *Investor sales* and *Negative ΔLendable* varies across different securities, depending on the level of their coupon. Namely, the predictive power of *Negative ΔLendable* is stronger among the securities with high coupon (above the credit rating category median), while *Investor sales* are a stronger predictor of performance for securities with low coupon.

This evidence is inconsistent with the informed broker hypothesis, while it confirms the informed investors hypothesis. It suggests that the predictive power of making securities available for lending is due to superior information (or greater ability to interpret public information) on part of the holders of these securities.

Conclusions

In illiquid markets, trading by "informed" investors can have limited predictive power, because trading volumes are low and may not be timely. In these conditions, changes in the lendable amounts of securities can act as a canary in a coalmine, and predict future performance when trading activity cannot.

We bring this argument to the data by focusing on the structured finance ("securitized bonds") segment. Trading in this segment typically occurs in OTC, illiquid markets, where information asymmetry considerations are of first-order economic relevance. We find strong evidence that changes in the amount of securities made available for lending predict the future performance (delinquency and foreclosure rates) of the underlying pool of loans in our sample securitized bonds. In contrast, we do not find any evidence of predictability from securities *borrowing*.

Our tests also show that investor trades have comparable predictive power to lending, supporting the hypothesis that securities holders (lenders), but not lending/borrowing intermediaries, possess material information in this market. Finally, consistent with our argument, we find that lending has stronger predictive power than trading in less liquid markets, proxied by securities with a larger coupon.

In a future draft of the paper, we plan to expand our results by considering more direct proxies for liquidity, based on actual trading activity. We also plan to investigate the channels through which securities lenders become informed. Another open question which we plan to investigate is the horizon of informed investors. In most of our tests, we have focused on predictive regressions with a one-month or one-quarter horizon. But it is possible (and indeed, figure 3 suggests it) that the predictive power of changes in lendable amounts stretch over a longer horizon.

Overall, these findings provide evidence on the information content of the securities lending market. To the best of our knowledge, they are the first to identify changes in lendable amounts as a signal of distress in the structured finance segment.

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Table I: Descriptive statistics

The table shows tranche-level descriptive statistics for our sample of 9,180 ABS and MBS from 3,973 deals issued between January 2000 and June 2010 which are reported in the DataExplorers database. *Δ90-day delinquency* and *ΔForeclosure rate* are monthly measures of deal-level performance, where *Δ90-day delinquency* refers to the monthly change in the fraction of loans that are more than 90 days delinquent and *ΔForeclosure rate* refers to the monthly change in the fraction of loans that are in foreclosure. *ΔUtilization ratio* is the monthly change in the tranche's utilization ratio, defined as total amount short sold divided by total amount lendable. *ΔLent (Lendable) / issue amount* is the monthly change in the amount lent (lendable) divided by initial issue amount. *HHI* is the weighted average Herfindahl Index of the investors holding the tranche. *Level of subordination* is defined following He et al. (2014) as the dollar-weighted fraction of tranches in the same deal that have a rating the same as or better than the given tranche. *Initial rating* is average rating assigned to the same tranche by the three rating agencies, converted to a numerical scale following Jorion, Liu, Shi (2005). *Weighted average life* is equal to the expected timing of payments of principal of a tranche. *Geographical concentration* of the collateral pool equals the sum of the squared shares of the collateral within a deal across each of the top five states (with the largest amount of mortgages), with the aggregation of all the other states as the sixth category. *Collateral in troubled states* equals the fraction of collateral originated in the states with the highest delinquency rates in the previous calendar month according to the Loan Performance database.

				Quantiles				
	N	**Mean**	**Stdev.**	**Min**	**0.25**	**Med**	**0.75**	**Max**
Performance measures								
Δ90-day delinquency rate (%)	501,029	0.27	1.21	-59.50	0.00	0.00	0.42	59.50
ΔForeclosure rate (%)	488,930	0.12	1.04	-50.97	0.00	0.00	0.16	100.00
Key explanatory variables								
ΔUtilization ratio (%)	811,736	0.00	5.00	-100.00	0.00	0.00	0.00	100.00
ΔLent / issue amount (%)	810,641	0.00	0.11	-1.81	0.00	0.00	0.00	1.81
ΔLendable / issue amount (%)	810,641	-0.21	4.71	-99.99	-0.31	-0.01	0.04	100.49
HHI (%)	783,447	0.90	1.46	0.03	0.17	0.45	1.08	19.10
Control variables								
Log issue amount	845,873	4.13	1.59	-9.21	3.13	4.11	5.30	12.26
Level of subordination (%)	658,055	87.87	11.34	0.00	82.50	91.25	96.10	100.00
Initial rating	844,636	2.54	2.65	1.00	1.00	1.00	3.00	18.00
Number of ratings	847,019	2.16	0.55	0.00	2.00	2.00	2.00	3.00
Wavg. Life	809,394	5.85	3.27	0.10	3.25	5.01	9.05	29.11
Median FICO score	360,427	694.09	57.40	0.00	677.00	712.00	731.00	788.00
Median FICO score missing	847,019	0.57	0.49	0.00	0.00	1.00	1.00	1.00
Geographic concentration	532,203	0.34	0.08	0.17	0.29	0.33	0.37	0.95
Collateral in troubled states	847,019	0.10	0.19	0.00	0.00	0.00	0.12	1.00

Table II: Short selling and lending as a function of security characteristics

The table reports the results from tranche-level regressions of (1) the utilization ratio, (2) amount short sold as a fraction of total issue amount, and (3) amount lendable as a fraction of total issue amount, on security and deal characteristics. Standard errors are clustered at the deal level.

	Utilization ratio	**Lent / issue amount**	**Lendable / issue amount**
	(1)	(2)	(3)
Log issue amount	0.520	0.016	-8.300
	(4.16)	(3.58)	(-12.95)
Level of subordination	-0.044	-0.001	-0.196
	(-2.06)	(-1.83)	(-4.39)
Initial rating	0.051	0.004	-0.574
	(0.51)	(0.94)	(-1.73)
Number of ratings	-0.267	-0.003	-1.100
	(-2.95)	(-0.51)	(-1.72)
Initial rating disagreement	-0.269	-0.011	-0.140
	(-1.70)	(-1.39)	(-0.15)
Wavg. Life	0.362	0.008	2.606
	(4.04)	(4.40)	(17.27)
Wavg. Coupon	-0.105	-0.004	-1.800
	(-1.26)	(-1.56)	(-6.08)
Geographic concentration of collateral	-5.300	-0.130	-21.000
	(-3.14)	(-2.41)	(-5.08)
Collateral in troubled states	3.225	0.079	-20.000
	(2.43)	(2.00)	(-1.52)
Median FICO score	0.005	0.000	0.030
	(1.38)	(1.39)	(4.26)
Median FICO score missing	2.799	0.054	19.000
	(1.30)	(1.34)	(3.86)
Median LTV	0.010	0.000	0.113
	(0.87)	(1.00)	(4.08)
Median LTV missing	2.208	0.053	6.932
	(2.07)	(1.51)	(2.86)
Percentage of ARM loans	-0.011	0.000	-0.067
	(-2.23)	(-1.10)	(-3.26)
Number of loans	0.000	0.000	0.000
	(-0.16)	(0.48)	(0.23)
Issuance quarter dummies	Yes	Yes	Yes
N	300,769	300,769	300,769
R^2	0.038	0.047	0.413

Table III: Predicting future performance with changes in the amount lendable

The table reports regressions of next month's change in the deal's 90-day delinquency rate (columns (1) and (2)) and next month's change in foreclosure rates (columns (3) and (4)) on changes in the amount lendable as a fraction of total issue amount, and controls. In Panel A, we collapse the data at the deal level by computing a weighted average across all tranches in the same deal (weights are proportionate to the tranche's share in the original deal amount). In Panel B, we run regressions at the individual tranche level. Standard errors are clustered around deal type × month in Panel A, and at the deal level in Panel B.

Panel A: Deal level

(Coefficients of interest multiplied by 100)

	Δ90-day delinquency rate t+1		**ΔForeclosure rate t+1**	
	(1)	(2)	(3)	(4)
ΔLendable / issue amount	-0.452	-0.457	-0.278	-0.207
	(-2.58)	(-2.47)	(-3.31)	(-2.70)
Log issue amount	0.009		0.004	
	(1.50)		(0.99)	
Number of ratings	-0.003		0.002	
	(-0.21)		(0.22)	
Log wavg. Life	-0.281		-0.111	
	(-10.93)		(-7.47)	
Median FICO score	0.000		0.000	
	(-5.50)		(-3.46)	
Median FICO score missing	-0.302		-0.142	
	(-7.94)		(-4.49)	
Geographic concentration of collateral	0.102		0.009	
	(0.75)		(0.12)	
Collateral in troubled states	-0.099		0.015	
	(-1.62)		(0.36)	
Deal type	Yes	No	Yes	No
Month fixed effects	Yes	Yes	Yes	Yes
Deal fixed effects	No	Yes	No	Yes
N	143,207	181,580	142,186	178,739
R^2	0.028	0.063	0.015	0.037

Panel B: Tranche level

(Coefficients of interest multiplied by 100)

	Δ90-day delinquency rate t+1		**ΔForeclosure rate t+1**	
	(1)	(2)	(3)	(4)
ΔLendable / issue amount	-0.196	-0.103	-0.133	-0.049
	(-3.54)	(-2.16)	(-2.95)	(-1.69)
Log issue amount	0.012	0.003	0.007	0.001
	(2.71)	(2.00)	(3.24)	(0.84)
Level of subordination	-0.013	0.000	-0.005	0.000
	(-13.87)	(1.04)	(-12.25)	(1.25)
Log wavg. Life	-0.127	-0.027	-0.051	-0.011
	(-12.59)	(-6.91)	(-10.05)	(-4.57)
Number of ratings	0.002		0.008	
	(0.12)		(1.26)	
Median FICO score	-0.001		-0.001	
	(-3.76)		(-3.37)	
Median FICO score missing	-0.971		-0.420	
	(-4.17)		(-3.88)	
Geographic concentration of collateral	-0.043		-0.055	
	(-0.75)		(-1.69)	
Collateral in troubled states	-0.221		-0.032	
	(-4.41)		(-1.19)	
Rating category	Yes	Yes	Yes	Yes
Deal type	Yes	No	Yes	No
Month fixed effects	Yes	Yes	Yes	Yes
Deal fixed effects	No	Yes	No	Yes
N	284,492	440,859	292,728	449,236
R^2	0.048	0.091	0.019	0.041

Table IV: Predicting future performance with changes in the amount lent

The table reports regressions of next month's change in the deal's 90-day delinquency rate (columns (1) and (2)) and next month's change in foreclosure rates (columns (3) and (4)) on changes in the amount lent as a fraction of total issue amount, and controls. In Panel A, we collapse the data at the deal level by computing a weighted average across all tranches in the same deal (weights are proportionate to the tranche's share in the original deal amount). In Panel B, we run regressions at the individual tranche level. Standard errors are clustered around deal type × month in Panel A, and at the deal level in Panel B.

Panel A: Deal level

(Coefficients of interest multiplied by 100)

	Δ90-day delinquency rate t+1		**ΔForeclosure rate t+1**	
	(1)	(2)	(3)	(4)
ΔLent / issue amount	1.378	0.499	1.050	0.196
	(0.48)	(0.27)	(0.48)	(0.17)
Log issue amount	0.009		0.004	
	(1.44)		(0.94)	
Number of ratings	-0.003		0.002	
	(-0.20)		(0.22)	
Log wavg. Life	-0.281		-0.111	
	(-10.93)		(-7.45)	
Median FICO score	0.000		0.000	
	(-5.50)		(-3.46)	
Median FICO score missing	-0.303		-0.142	
	(-7.95)		(-4.49)	
Geographic concentration of collateral	0.102		0.008	
	(0.74)		(0.11)	
Collateral in troubled states	-0.098		0.015	
	(-1.61)		(0.37)	
Deal type	Yes	No	Yes	No
Month fixed effects	Yes	Yes	Yes	Yes
Deal fixed effects	No	Yes	No	Yes
N	143,207	181,580	142,186	178,739
R^2	0.028	0.063	0.015	0.037

Panel B: Tranche level

(Coefficients of interest multiplied by 100)

	Δ90-day delinquency rate t+1		**ΔForeclosure rate t+1**	
	(1)	(2)	(3)	(4)
ΔLent / issue amount	-1.548	0.298	-0.351	0.016
	(-1.31)	(0.56)	(-0.35)	(0.04)
Log issue amount	0.011	0.003	0.007	0.001
	(2.65)	(1.92)	(3.16)	(0.78)
Level of subordination	-0.013	0.000	-0.005	0.000
	(-13.87)	(1.05)	(-12.26)	(1.26)
Log wavg. Life	-0.127	-0.027	-0.051	-0.011
	(-12.59)	(-6.91)	(-10.05)	(-4.57)
Number of ratings	0.001		0.008	
	(0.11)		(1.25)	
Median FICO score	-0.001		-0.001	
	(-3.76)		(-3.37)	
Median FICO score missing	-0.971		-0.420	
	(-4.17)		(-3.88)	
Geographic concentration of collateral	-0.043		-0.055	
	(-0.75)		(-1.70)	
Collateral in troubled states	-0.222		-0.032	
	(-4.41)		(-1.19)	
Rating category	Yes	Yes	Yes	Yes
Deal type	Yes	No	Yes	No
Month fixed effects	Yes	Yes	Yes	Yes
Pool fixed effects	No	Yes	No	Yes
N	284,492	440,859	292,728	449,236
R^2	0.048	0.091	0.019	0.041

Table V: Positive vs. Negative Changes in Lendable

The table presents results for positive vs. negative changes in lendable. In Panel A, we collapse the data at the deal level by computing a weighted average across all tranches in the same deal (weights are proportionate to the tranche's share in the original deal amount). In Panel B, we run regressions at the individual tranche level. Standard errors are clustered around deal type × month in Panel A, and at the deal level in Panel B.

Panel A: Positive vs. negative changes in lendable – deal level

	Δ90-day delinquency rate		**ΔForeclosure rate**	
	ΔLendable > 0	ΔLendable < 0	ΔLendable > 0	ΔLendable < 0
	(1)	(2)	(3)	(4)
ΔLendable	0.028	-1.196	0.011	-0.623
	(0.09)	(-6.52)	(0.10)	(-4.36)
Deal Controls	No	No	No	No
Deal type	No	No	No	No
Month fixed effects	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes
N	41,258	99,227	40,769	98,446
R^2	0.035	0.031	0.020	0.018

Panel B: Positive vs. negative changes in lendable – tranche level

	Δ90-day delinquency rate		**ΔForeclosure rate**	
	ΔLendable > 0	ΔLendable < 0	ΔLendable > 0	ΔLendable < 0
	(1)	(2)	(3)	(4)
ΔLendable	0.077	-0.290	0.002	-0.076
	(0.93)	(-3.24)	(0.04)	(-1.76)
Controls	Yes	Yes	Yes	Yes
Deal type	No	No	No	No
Month fixed effects	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes
N	84,792	278,980	87,050	284,479
R^2	0.057	0.109	0.021	0.052

Table VI: Sample Splits by Coupon Size

The table presents quarterly tranche-level regressions when the sample is split by coupon size. *Negative ΔLendable* is the absolute change in lendable if that change is negative, and zero otherwise. *Investor Sales* is calculated as the percentage of institutional investors who decrease the weight of the security in their portfolio during the current quarter. Quarterly changes in delinquency (foreclosure) rates are computed as the average monthly changes in delinquencies (foreclosures) during a given quarter. High/Low Coupon is split at the median in a given rating category. Standard errors are clustered at the deal level.

Panel A: Changes in Lendable

	Δ90-day delinquency rate t+1			**ΔForeclosure rate t+1**		
	All	Low Coupon	High Coupon	All	Low Coupon	High Coupon
	(1)	(2)	(3)	(4)	(5)	(6)
Neg. ΔLendable	0.376	0.332	0.351	0.107	0.057	0.196
	(3.94)	(1.66)	(3.56)	(1.37)	(0.38)	(2.25)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Qtr fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	144,124	66,228	77,896	146,714	67,687	79,027

Panel B: Investor Sales

	Δ90-day delinquency rate t+1			**ΔForeclosure rate t+1**		
	All	Low Coupon	High Coupon	All	Low Coupon	High Coupon
	(1)	(2)	(3)	(4)	(5)	(6)
Investor Sales	0.044	0.068	0.010	0.024	0.039	0.002
	(5.92)	(4.72)	(1.49)	(3.44)	(2.75)	(0.28)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Qtr fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	78,316	34,103	44,213	80,301	35,126	45,175

Panel C: Both Changes in Lendable and Investor Sales

	Δ90-day delinquency rate t+1			**ΔForeclosure rate t+1**		
	All	Low Coupon	High Coupon	All	Low Coupon	High Coupon
	(1)	(2)	(3)	(4)	(5)	(6)
Neg. ΔLendable	0.105	-0.081	0.222	0.143	0.182	0.113
	(1.12)	(-0.46)	(2.01)	(1.75)	(1.09)	(1.35)
Investor Sales	0.041	0.063	0.008	0.025	0.041	0.002
	(5.47)	(4.27)	(1.14)	(3.55)	(2.81)	(0.25)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Qtr fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	76,198	33,263	42,935	78,116	34,254	43,862

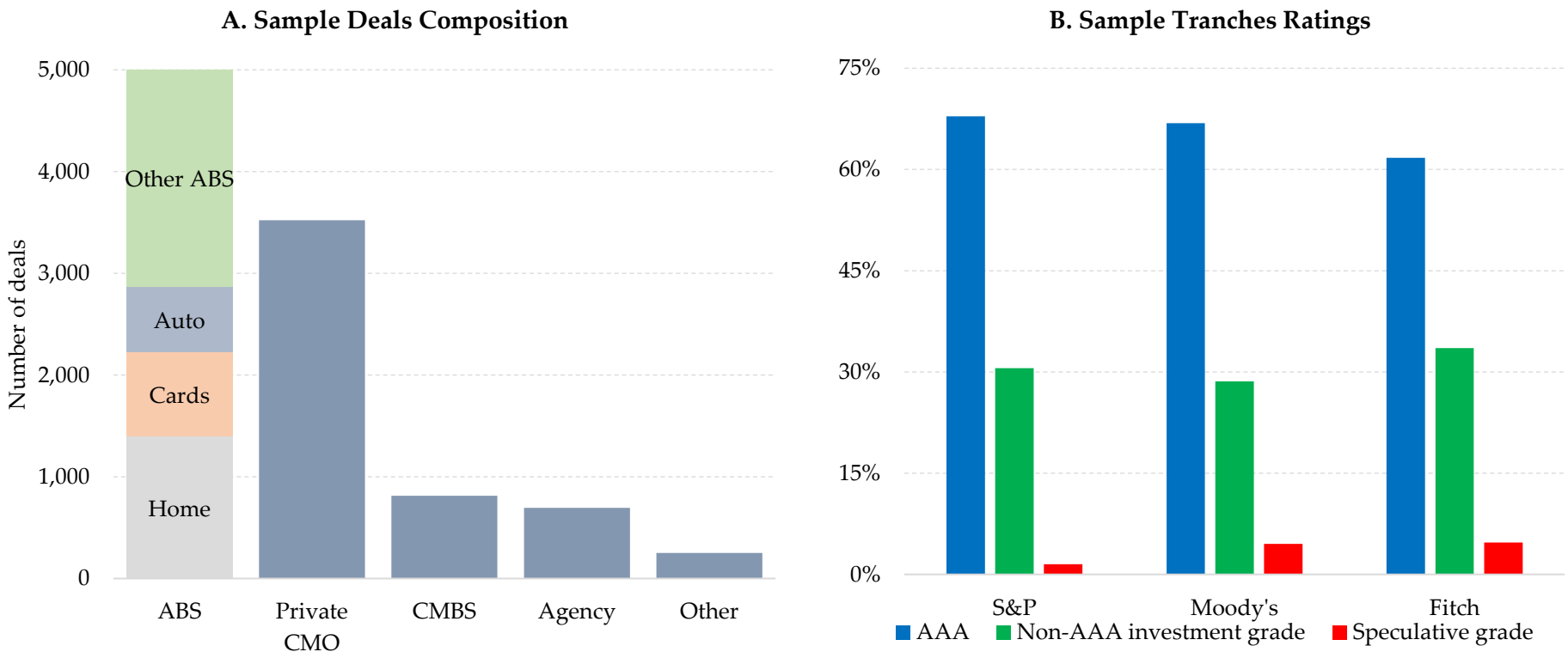

Figure 1 Sample composition

In panel A, the chart describes the types of deals represented in our sample, categorized as ABS (broken down into Auto, Cards, Home, and Other), private CMO, CMBS, Agency, and a residual category. Panel B breaks down the sample tranches by their S&P, Moody's, and Fitch rating.

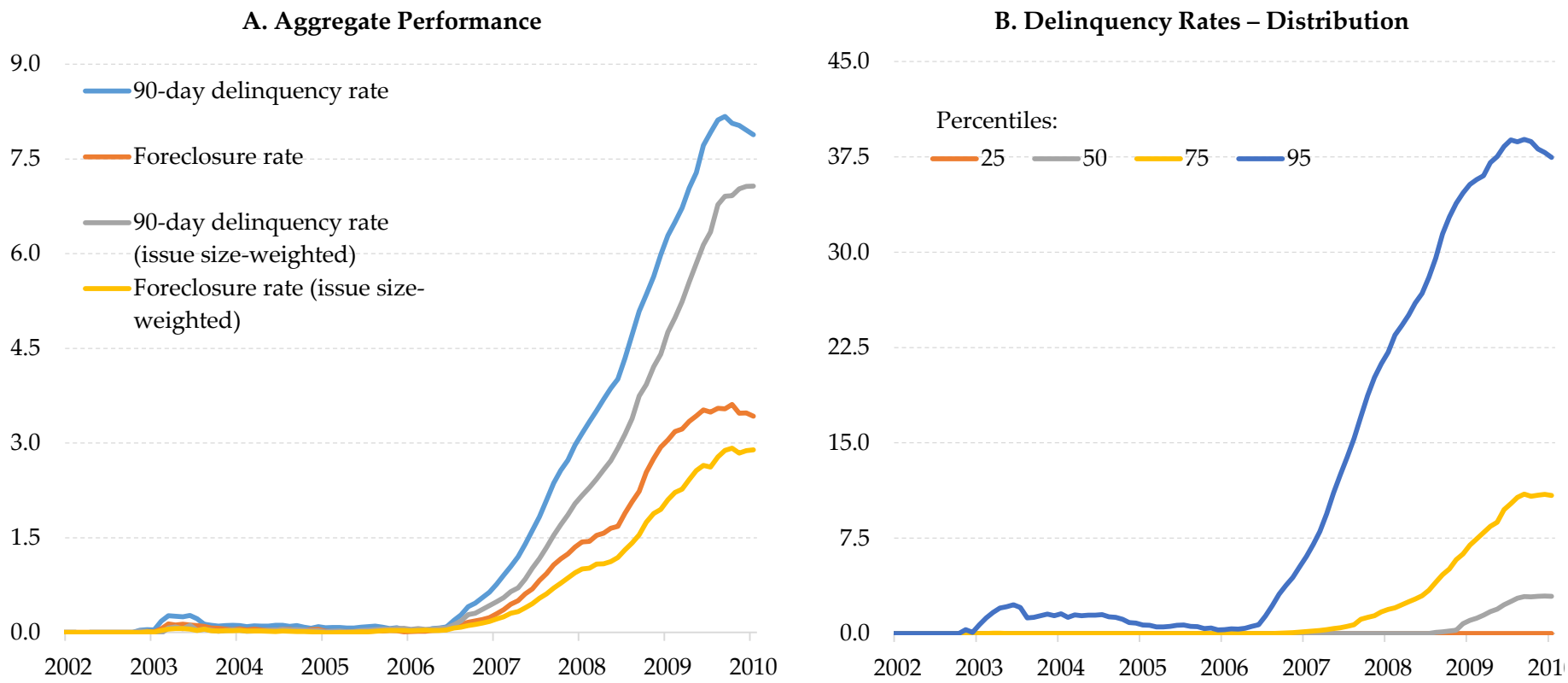

Figure 2 Performance of the sample deals

Panel A plots the aggregate performance of the sample deals, in terms of *90-day delinquency* and *Foreclosure rate*, both in equal-weighted and issue size-weighted average terms. Panel B plots the 25th, 50th, 75th, and 95th percentiles of the distribution of *90-day delinquency rates* over time.

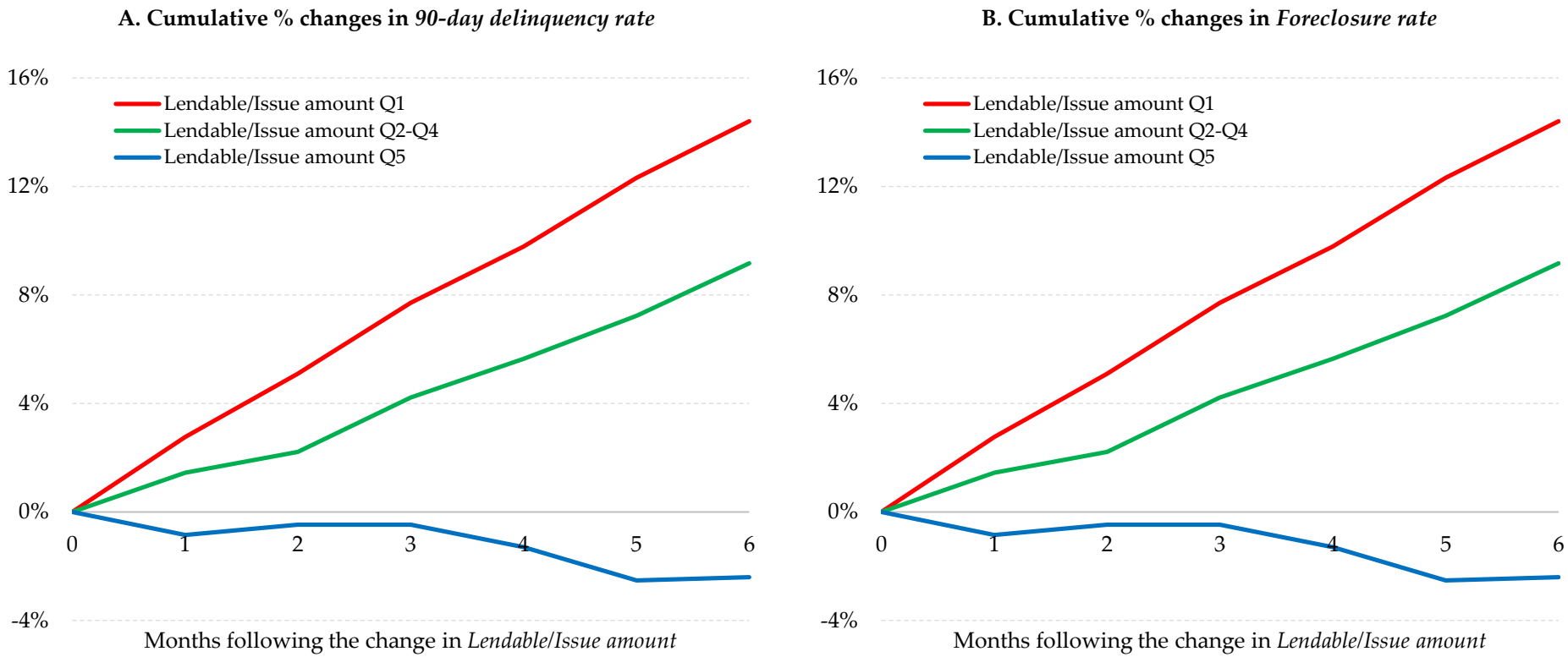

Figure 3 Performance changes following changes in *Lendable/Issue amount*

The graph shows the evolution of delinquency and foreclosure rates in our sample deals, following changes in *Lendable/Issue Amount*. Each calendar month, deals are sorted based into quintiles on the change in *Lendable/Issue amount* relative to the previous months. *90-day delinquency rates* (panel A) and *Foreclosure rates* (panel B) are then averaged within quintile groups (quintiles 2, 3, and 4 are grouped together), and tracked over 6 months following the change in *Lendable/Issue amount*. Each line in panel A plots the difference between the log-average *90-day delinquency rate* on month $t = 1, \ldots 6$ and the log-average *90-day delinquency rate* on month 0, and can thus be interpreted as a percentage change. Panel B plots *Foreclosure rates* analogously. The graph indicates that drops in *Lendable/Issue amount* are associated with increasing *90-day delinquency rates* (*Foreclosure rates*) over the subsequent 6 months.