Canary in a Coalmine: Securities Lending Predicting the Performance of Securitized Bonds

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Abstract

We study the information content of the "cash-driven" side of the securities lending market. We focus on the structured finance products ("securitized bonds") segment, where confounding effects from short selling are less likely. We document that changes in lendable amounts, proxying for the amount of a security used as collateral in a cash loan, predict future performance (delinquencies, foreclosure rates, and deal losses). Decreases in lendable amounts act like the proverbial canary in a coalmine, predicting a worsening performance. In contrast, we do not find any evidence of predictability from changes in the on loan amounts. This evidence is consistent with securities lenders/cash borrowers and/or lending intermediaries possessing information about the future value of the securities.

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Introduction

The past two decades have witnessed the rise of securities lending as a global phenomenon. The securities lending market has quickly developed since the early 2000s, reaching several trillions of dollars on loan and many more available for lending or used as collateral in cash loans, and it is now close in size to its pre-crisis peak (Dive, Hodge, and Jones (2011)). Increasingly, securities lending is an important component of the business model, and a sizeable source of funding, for a range of large institutional investors, including insurance companies (Foley-Fisher, Narajabad, and Verani (2015)) and investment advisors (Evans, Ferreira, and Prado (2017)).

Securities lending involves the temporary transfer of a security from a lender to an intermediary or a borrower, typically against cash or other securities. Securities lending transactions can be "securities-driven," where a security is borrowed for a fee, typically to facilitate a short sale. Alternatively, they can be "cash-driven," where an investor borrows cash from an intermediary, providing securities as collateral on the loan. So far, the literature has largely focused on securities-driven transactions, as a source of information and a driver of market efficiency via short selling.[1]

Cash-driven securities lending transactions have received much less attention. There are, however, economic reasons to expect that they should be just as relevant and reflect fundamental information, as lending *intermediaries* and the *lenders* themselves may be informed. First, securities lenders who borrow cash via this channel are typically large institutional investors, with specialized knowledge and resources to monitor their portfolio holdings (Herring and Schuermann (2005)). We should thus expect them to possess information regarding the value of their securities as collateral. In particular, they will seek to sell a security, rather than use it as collateral, if they expect its performance to deteriorate. Second, lending intermediaries, being the nexus of a number of different transactions, can extract a more precise signal about the future value of the securities from the aggregate order flow (e.g., Kyle (1985)), and refuse to accept a

[1] An early argument that short-sale constraints can limit price efficiency was made by Miller (1977). There is a vast empirical literature on short selling, too large to summarize here; an excellent review is provided by Reed (2013).

security as collateral if they expect its performance to worsen. In this paper, we provide new evidence consistent with the cash-driven transactions/collateral channel.

To run our test, we focus on securities lending in the structured finance (henceforth, "securitized bonds") segment. 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.

The features of the structured finance segment provide us with a relatively clean setting to take our arguments to the data, for at least two reasons. First, anecdotal evidence suggests that short selling in this segment is potentially very costly and not widespread (e.g. Lewis (2010)). Thus, focusing on structured finance helps us isolate the cash-driven transactions channel, and attenuates the likelihood of a confounding effect of securities lenders responding to demand (or expected demand) from short sellers. Second, industry practice suggests that the use of fixed-income securities, including structured finance products, as collateral in cash-driven securities lending is common and economically substantial (Baklanova, Copeland, and McCaughrin (2015), IOSCO (1999)).

In addition, understanding who are the informed market participants in structured finance is especially relevant, because this is a segment where information asymmetry considerations are central. 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 lendable amounts

("*Lendable*") and the future performance of securitized bonds' underlying pool of loans.[2] Like the proverbial canary in a coalmine, a drop in *Lendable* on a given security 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 2 percentage points increase in delinquency rates, and a 80 basis points increase in foreclosures, in their underlying pool of loans. In comparison, median delinquency (foreclosure) rates are around 15% (6%) in early 2009, at the height of the financial crisis; these effects are thus economically substantial. 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), and many others). 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 one possible economic mechanism underlying the predictive power of changes in lendable amount 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

[2] The data provider (Markit, formerly DataExplorers) aggregates securities-driven and cash-driven securities lending transactions. For that reason, it labels the sum of the amount of a security being used as collateral in a financing transaction plus the amount that is simply available to be borrowed as "lendable quantity". We follow the terminology of the data provider. Representatives from Markit have clarified to us that the lendable quantity comprises cash-driven financing transactions; however, a breakdown between securities- and cash-driven transactions is not available to us.

investors (Manconi, Massa, and Yasuda (2012)). Their information advantage allows them to forecast a worsening performance of the securities, and react by liquidating their positions. This will generate a drop in lendable amount in anticipation of a worsening performance.

A second possible explanation is the *informed intermediaries hypothesis* that it is not the securities holders, but rather the lending 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 from the order flow. When the intermediary forecasts worsening performance for a given security, she will no longer be willing to accept it as collateral for lending cash. 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, 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 re-hypothecation 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)).

These two hypotheses, moreover, are not mutually exclusive: it may well be that informed lenders and intermediaries co-exist. The question is therefore to assess their relative economic importance. At the time of writing (May 2017), a complete set of tests distinguishing between the two hypotheses is not yet available; we plan to extend the analysis in that direction in the next draft of the paper.

Our preliminary tests focus on the informed lenders hypothesis. One possibility is that institutional investors are generally informed about the quality of structured finance products, and some just happen to be securities lenders. Alternatively, only investors who participate in the securities lending market possess superior information. Under the first scenario, trades by the average investor should absorb the predictive power of changes in lendable amounts; under the alternative scenario, they should not. Our results are consistent with the alternative scenario, suggesting that a core group of investors – the securities lenders/cash borrowers – possess superior information compared to the average institutional investor. Working towards the draft of the paper, we are directing our efforts towards characterizing these investors, and understanding through what channel(s) they acquire their information. In particular, we plan to build on the growing literature on information flows in financial conglomerates, and test whether being affiliated with a security underwriter can provide information to the lenders.

We also plan to analyze the informed intermediaries hypothesis more directly. Building on recent results that suggest that brokers can act as a conduit for spreading information in the stock market (Di Maggio, Franzoni, Kermani, and Sommavilla (2016)), we plan to test whether the predictive power of changes in lendable amounts is concentrated among securities that are typically traded through more "central" brokers. Data on structured finance securities trading, containing information about the brokers, is available at NAIC, and we are currently working on this test, which we plan to report in the next draft.

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 trading activity on securities, such as insider trading (Seyhun (1992), Meulbroek (1992)), or the trades of short sellers (Cohen, Diether, and Malloy (2007), Saffi and Sigurdsson (2011), Engelberg, Reed, and Ringgenberg (2012)). Given the conditions of low liquidity and limited trading volumes that prevail among structured finance products, actual informed trading on securities markets may be hindered. We show that informed trading activity still appears to take place in the securities *lending* market (likely, in the market for using securities as financing collateral).

Second, it contributes to the growing literature on securities lending. While a large body of has research 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 studies has started to fill this gap. Foley-Fisher, Narajabad, and Verani (2015) and Evans, Ferreira, and Prado (2017) 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, and discussed potential interpretations. Section IV considers two economic mechanisms explaining the predictability result, based on the informed intermediaries and lenders hypotheses. 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 Markit (formerly DataExplorers) securities lending database.

A. Structured finance products

We now briefly describe the structure of the structured finance securities ("securitized bonds") in our sample. Each issue (henceforth, "deal") is based on the securitization of 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 deal is then broken down into a number of tranches, creating different classes of securities from the same pool of loans, and allowing the cash flows from the loans to reach different groups of investors. Different tranches have 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 structured finance products 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. The securities lending market

We obtain securitized bonds lending data from Markit (formerly DataExplorers), a privately owned company that supplies financial benchmarking information to the securities lending industry and short-side intelligence to investment managers. Markit 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, Markit reports the lendable quantity (in $1,000 par amount value) and the total on loan balance quantity (in $1,000 par amount value) at monthly frequency.[3]

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)). Securities lending can be, in general, *securities-driven* or *cash-driven*. In a securities-driven transaction, 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 average security, comparable to the 99% reported by Asquith, Au, Covert, and Pathak (2013) for the corporate bond market. The security borrower, thus, 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.

[3] 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 Markit 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.

In a cash-driven transaction, securities are used as collateral to raise short-term finance. The cash lender generally is not looking for a specific security, but will fund the cash borrower (security lender) against securities within defined categories of "general collateral" – examples may be government bonds, as well as highly-rated fixed income securities. The cash borrowers use these transactions to finance their portfolios, and are able to do so at rates generally below uncollateralized lending rates. Cash-driven transactions are referred to as (a) repurchase agreements, also known as "repo", where one party agrees to sell another party securities against cash, with the simultaneous agreement to repurchase the same or equivalent securities at a specific price, at a later date; or (b) sell-buyback agreements, which have an identical cash flow structure, but where the sell and buy trades are legally separate contracts. Sell-buyback agreements are typically less documented, do not involve margins, and are a form of financing trade limited to fixed income securities, including structured finance products.

The Markit 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 2.3% of NYSE and AMEX market cap (D'Avolio (2002)) or about one third of share trading volume on NYSE and NASDAQ (Diether, Lee, and Werner (2002)). Asquith, Au, Covert, and Pathak (2013) report that corporate bond borrowing amounts to 1.3% of the total outstanding amount, which, at an average daily par value of borrowed corporate bonds of $3.3 Bn, represents 19% of all corporate bond trades. The average daily par value of securitized bonds on loan in our sample is $103 million, consistent with the impression among practitioners that the market for borrowing securitized bonds is smaller than those for stocks and corporate bonds.[4]

The picture is very different, however, when we look at lendable amounts, i.e. securities that are either available for lending, or are being used as collateral in a cash-driven financing transaction. Saffi and Sigurdsson (2011) report that equity lendable amounts as a fraction of outstanding amounts average 20%. For corporate bonds, however, lendable amounts are only

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

about 3% of outstanding amount (Asquith, Au, Covert, and Pathak (2013)). In contrast, we find that lendable is on average about 7% of outstanding amounts during our sample period, i.e. over twice as much as in the corporate bond market.[5] These patterns suggest that, while securities-driven transactions are the main driver of securities lending in the equities and potentially in corporate bond markets too, among structured finance products cash-driven transactions are much more important.

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.

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

The change in *90-day delinquency*, *Foreclosure rate*, and *Cumulative deal losses* 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. The change in *Cumulative deal losses* refers to the monthly (or quarterly) change in the principal balance write-offs due to defaults. An increase in any of these measures, thus, implies a worsening performance for the entire deal.

Compared to more standard measures of performance such as market prices or returns, the delinquency and foreclosure rates and deal losses 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

[5] In 2006, Markit (then DataExplorers) increased the coverage of their data, including information from a broader range of custodian banks. If we compute the lendable-to-outstanding amount ratio in the post-2006 period, it is on average about 10%.

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.

On average, *90-day delinquency rates* (*Foreclosure rate*, *Cumulative deal losses*) in our data are 7.97% (3.34%, 1.50%). The average monthly change in *90-day delinquency rate* (*Foreclosure rate*, *Cumulative deal loss*) is 0.27% (0.12%, 0.09%, Table I), with a standard deviation of 1.21% (1.04%, 0.30%). 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 bonds in our sample began to worsen on average in 2007, reaching a peak in 2009, with median delinquency rates of about 15%, foreclosure rates of about 6%, and deal losses (write-offs) of about 2%.

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

Throughout the analysis, we mainly focus on *90-day delinquency rates*, as this is the more timely measure of performance and is treated by courts as the start of the default process (a default notice can be filed after 90 days of delinquency), e.g. for mortgages underlying the MBS securities in our data. We will report results for *Foreclosure rates* and *Cumulative deal losses* in robustness checks.

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 Markit 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*, computed for a given tranche as:

$$\log(Lendable\ quantity) \tag{1}$$

The quantity available for lending is obtained from Markit; quantity of a given security is measured in thousands of dollars of par-amount. This variable measures the supply of the security available for lending at a given point in time.

The second one is *On loan*, computed for a given tranche as:

$$\log(On\ loan\ quantity) \tag{2}$$

The quantity on loan is obtained from Markit, 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:

$$100 \times \frac{On\ loan\ quantity}{Lendable\ quantity} \tag{3}$$

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*, *On loan*, 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, rating, collateral type (the nature of the underlying pool of loans), as well as creditworthiness of the underlying loans, proxied by median FICO score, geographic concentration of collateral, in particular in "troubled" U.S. states especially exposed to the subprime crisis (He, Qian, and Strahan (2014)).

Specifications (2) and (3) in Table II indicates that, similar to the corporate bond market (Asquith, Au, Covert, and Pathak (2013)), securitized bonds are more likely borrowed when they are larger, and when they have a longer time to maturity. Unlike corporate bonds, however, the relationship between borrowing and default risk is weak or ambiguous: FICO scores do not have a significant association with either *On loan amount* or *Utilization ratio*, the percentage of underlying loans associated with "troubled" states is positively associated with *Utilization ratio*, and a better initial rating is associated with higher *Utilization ratio*.[6] In other words: borrowing of structured finance products does not have a strong association with proxies for default risk, and when there is an association, lower-risk bonds are more likely borrowed. This suggests that securities borrowing is unlikely used to facilitate a short sale in the structured finance segment.

In contrast, specification (1) 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

[6] Following the numerical conversion adopted by Jorion, Liu, and Shi (2005), a higher value of the *Initial rating* variable is associated with a worse rating. Ratings range from 1 (AAA Standard and Poor's or Fitch/Aaa Moody's) to 23 (default).

geographically concentrated underlying loans, and a better initial rating 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 rates*. 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 lendable amounts do not predict an improving performance. We discuss two potential interpretations of these findings, pointing to two distinct, but not mutually exclusive, 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* 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 tercile, experiencing the largest decrease in *Lendable*, exhibit a 2 percentage points increase in *90-day delinquency rate*, and an 80 basis points increase in *Foreclosure rate*, over the subsequent 6 months. In contrast, deals in the top tercile display little to no change in performance over the same horizon.

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

$$Perf_{it+1} = \alpha + \beta \, \Delta Lendable + \gamma' x_{it} + \varepsilon_{it} \tag{4}$$

where $Perf_{it+1}$ denotes the monthly change in *90-day delinquency 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* are only available at the deal level.

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* is replaced by *On loan and Utilization ratio*. 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* and next-month performance, measured by the change in *90-day delinquency*.

The effects are also economically meaningful: they imply that a 10% decrease in lendable amount is associated with a rise in the *90-day delinquency* rate by 21-47 basis points the next month.[7] For the average security in our sample, the *90-day delinquency rate* is approximately 8%; therefore, a 10% decrease in lendable amount is associated with a decrease in delinquency rates of 3-5% relative to the average deal. These results confirm the intuition of Figure 3, and suggest that the effects implied by our estimates are indeed economically substantial.

They also hold across both deal- (columns (1)-(2)) and tranche-level (columns (3)-(4)) 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 specifications (3)-(4) in Table III 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 on loan amount do not predict future performance. For the proxies for securities lending considered here, *On loan* and *Utilization ratio*, the coefficient estimates reported in Table IV are either statistically indistinguishable from zero (specifications (3)-(4)) or at best marginally significant (specifications (1)-(2)). Importantly, even the direction of the implied effects (leaving aside their statistical significance) is unexpected: an increase in *On loan* amount (*Utilization ratio)* is associated with a *decrease* in *90-day delinquency rate*. In other words, a greater on-loan amount (greater security borrowing) is associated with an improving, not a deteriorating, performance.

This is consistent with the evidence of a weak relationship between on-loan amounts and default risk discussed in section II, as well as with some of the findings of Asquith, Au, Covert, and Pathak (2013) suggesting that securities lending in the fixed income market is not typically

[7] These effects are estimated as follows. The coefficient on *Lendable* in Table III, column (1), is –0.047; multiplying that by –0.10, we obtain the 47 basis points increase in *90-day delinquency rate*. Likewise, the coefficient in column (4) is –0.021; multiplying that by –0.10, we obtain a 21 basis points increase. Economic effects are computed analogously throughout the paper.

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, in comparison 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 default swaps – consistent with popular accounts of the 2007-8 financial crisis such as Lewis (2010).

The finding that changes in *Lendable* predict performance is robust to a number of robustness checks, described in Table V. First, our baseline result considers a prediction horizon of one month. In Table V, we show that changes in lendable amounts on a given month predict performance over longer horizons too, for 3 and 6 months, consistent with the evidence of Figure 3. Second, we can detect predictability on alternative measures of performance, the *Foreclosures rate* and *Cumulative deal losses*; the latter measure is especially relevant, as it gauges the principal write-offs due to defaults on the pool of loans underlying a given security. Third, the results are stable over different periods in our sample. We detect a stable, negative relationship between changes in *Lendable* and changes in delinquency rates over the early period 2002-2005, the runup to the crisis 2006-2008, and the aftermath of the crisis 2009-2010.

Fourth and final, we perform an additional test dissecting the predictability results reported in Table III. We estimate equation (4) on two sub-samples, corresponding to increases and decreases in *Lendable*. We find that it is exclusively *negative* changes in the lendable amount that predict worsening performance. The economic effects implied by these estimates are also larger: a 10% decrease in *Lendable* is associated with an increase in *90-day delinquency rate* 60 basis points, or 7.5% relative to the average deal. A comparable increase in lendable, in contrast, predicts an improvement in performance by an economically much more modest 13 basis points, statistically indistinguishable from zero. The implication of these estimates is that changes in *Lendable* are 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* is an indicator that can be measured in real time. This makes it at least in principle, a 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)).[8] There are two possible explanations, each related to the unique features of the structured finance 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. Based on 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.

[8] In a future draft of the paper, we plan to examine directly the equity and corporate bond markets, to understand if similar effects can be detected there. Given that, at least for the equity markets, there is evidence that securities *borrowing* predicts performance, the inference in that case is complicated by the simultaneous movements in demand and supply in the securities lending market. As we mentioned in the introduction, that is less of an issue in the structured finance segment, because on-loan amounts are generally very small, as our data confirm.

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. Indeed, Di Maggio, Franzoni, Kermani, and Sommavilla (2016) show that "central" brokers contribute to the diffusion of information in the stock market. 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 Investors and Informed Intermediaries

The two interpretations discussed above need not be mutually exclusive. In fact, the information possessed by informed intermediaries may derive in part from trades they make with informed traders, and vice versa. Thus, our results strongly suggest that the securities *borrowers* are not informed; but when it comes to comparing securities lenders and intermediaries the question is more one of relative economic importance.

A. Informed investors

To the extent that the predictability result is due to superior information (or information processing ability) on part of the structured finance securities lenders/institutional investors, 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 evidence in the literature that the trades of institutional investors contain information that predicts performance, e.g. in equity markets (e.g., Baker, Litov, Wachter, and Wurgler (2010), Puckett and Yan (2011)). Importantly, two alternative scenarios can lead to *Lendable* predicting performance:

(A) All institutional investors are informed about future performance, and at least some of them are securities lenders. If that is the case, investor trades should subsume the predictive power of changes in lendable amounts.

(B) Institutional investors who participate in the securities lending market as lenders are informed, or have superior information compared to other investors. If that is the case, changes in lendable amounts should subsume any predictive power of investor trades.

We take these ideas to the data by running a "horse race" between changes in *Lendable* and investor trades. As a proxy for investor trading activity we consider *Investor trades*, defined for a given security at a given calendar quarter as the average change in the weight of the security in the portfolio of all investors covered in the Lipper eMAXX database.[9] We then run specifications analogous to equation (4), using changes in *Lendable* and *Investor trades* as the main explanatory variables.

The results of the test are reported in Table VI. The results are similar across the deal- (Panel A) and tranche-level (Panel B) estimates. Consistent with the evidence discussed so far, quarterly changes in *Lendable* predict performance. Furthermore, *Investor trades* also have predictive power: one percentage point decrease in the holdings of the average investor is associated with a 96 basis points increase in *90 day delinquency rate*. However, when both *Lendable* and *Investor trades* are included in the regression, the coefficient on *Investor trades* becomes statistically insignificant, and the associated economic effects drop in magnitude by about one half. In contrast, the predictive power of changes in *Lendable* is largely unchanged.

These findings suggest a picture closer to scenario (B) outlined above. A core group of investors, who participate in the securities lending market as lenders, appear to possess more predictive power than the average investor in the market for structured finance products.

In a future draft of the paper, we plan to identify what class(es) of investors are included in such core group. One possibility is investors affiliated with a financial conglomerate underwriting structured finance products. A growing literature suggests that, despite the presence of "Chinese walls," important information flows take place within financial

[9] Because institutional holdings from Lipper eMAXX are only available on the quarterly frequency, we look at changes in lendable amounts and portfolio weights on that frequency.

conglomerates (Massa and Rehman (2008), Ferreira, Matos, and Pires (2014), Gil-Bazo, Hoffman, and Mayordomo (2017)). Affiliated investors might acquire information about the quality of a given deal from the deal's underwriter, enabling them to make more informed trades. We are in the process of collecting data on investor affiliation, while will enable us to test this conjecture.

B. Informed intermediaries

As we discuss above, an additional possibility is that intermediaries are informed, and by refusing to accept a given security as collateral they drive changes in lendable amounts that predict performance. This alternative is potentially very relevant, given the central role that collateralized lending plays in financial markets. Typically, we assume that collateralized lending matters mainly as a source of leverage for investors (Brunnermeier and Pedersen (2009)); the "informed intermediaries" hypothesis suggests that it can also be a channel for information.

At the time of writing (May 2017), we have not yet taken this hypothesis to the data. Information on trades by insurance companies with their brokers is, however, available from the National Association of Insurance Commissioners (NAIC). We plan to use this information to test our hypothesis.

First, we plan to run tests in the spirit of Di Maggio, Franzoni, Kermani, and Sommavilla (2016) to understand if trades that go through more "central" brokers have more predictive power for performance in the structured finance market. Second, we plan to combine this information with our earlier results, to test if the predictive power of changes in *Lendable* is driven by securities primarily traded through "central" brokers. We plan to include the results of these tests in a future draft of the paper.

Conclusions

Although the literature has devoted much attention to the "securities-driven" side of the securities lending market, e.g. regarding its impact on price efficiency via short selling, much less is known about the "cash-driven" side of securities lending, where an investor borrows cash, using securities as collateral on the loan. In this paper, we investigate its information content. We focus on the structured finance segment, where confounding effects from short selling are less likely, and evidence from the industry suggests that collateralized borrowing is common.

We document that changes in lendable amounts, proxying for the amount of a security used as collateral in a cash loan, predict future performance (delinquencies, foreclosure rates, and deal losses). Decreases in lendable amounts act like the proverbial canary in a coalmine, predicting a worsening performance. In contrast, we do not find any evidence of predictability from changes in the on loan amounts, consistent with anecdotal evidence that short selling is not common in this market. Our results suggest that securities lenders/cash borrowers and/or lending intermediaries possessing information about the future value of the securities.

At the time of writing (May 2017), several open questions remain, which we plan to address in a future draft of the paper. In the first place, our suggests that a core group of investors, participating in the securities lending market as lenders/cash borrowers, are better informed than the average institutional investor active on structured finance products. We are working on tests to characterize who these informed investors might be, and through what channel(s) they acquire their superior information. One channel we plan to investigate is information flows within financial conglomerates. Affiliation with the underwriter of a given deal, for instance, could provide the investor with superior information about the quality and the likelihood of delinquencies of the underlying pool of loans. We have been collecting data on investor affiliation, and will make use of them in tests to be presented in the next draft.

Another open question which we plan to investigate is the role of intermediaries. Our results are, indeed, also consistent with the market acquiring information from intermediaries, who by refusing to accept a given security as collateral drive changes in lendable. This would be in line with recent findings in the literature, which suggest that "central" brokers play an important role in diffusing information in the market (Di Maggio, Franzoni, Kermani, and Sommavilla (2016)). Our proposed test will shed light on the role of collateralized lending as a potential channel for information diffusion by brokers.

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. Moreover, they are consistent with the view that, in illiquid *securities* markets where trading volumes are thin and potentially contain little information, the *collateral* market can have substantial information content.

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Table I: Descriptive statistics

The table shows tranche-level descriptive statistics for our sample of 27,003 ABS and MBS from 8,503 deals issued between August 2002 and June 2010 which are reported in the Markit (formerly DataExplorers) database. *Δ90-day delinquency, ΔForeclosure rate, and ΔCumulative Deal losses* 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, *ΔForeclosure rate* refers to the monthly change in the fraction of loans that are in foreclosure, and *ΔCumulative deal losses* refers to the monthly change in the total principal balance write-offs due to default. *ΔLog amount lendable (lent)* is the monthly change in the logarithm of the amount lendable (lent). *Issuance amount* refers to the principal amount of the tranche. *Weighted average life* is equal to the expected timing of payments of principal of a tranche. *Geographic HHI* 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. *Pct. of 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. *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).

				Quantiles				
	N	**Mean**	**St. dev.**	**Min**	**0.25**	**Median**	**0.75**	**Max**
Performance variables (%)								
ΔDelinquency rate	527,069	0.27	1.22	-59.50	0.00	0.00	0.42	59.50
ΔForeclosure rate	518,390	0.12	1.04	-50.97	0.00	0.00	0.16	78.41
ΔCumulative deal losses	270,748	0.09	0.30	-18.30	0.00	0.00	0.02	27.00
Delinquency rate	586,434	7.97	12.52	0.00	0.00	1.68	10.53	59.50
Foreclosure rate	574,403	3.34	5.73	0.00	0.00	0.35	4.40	82.68
Cumulative deal losses	311,154	1.50	3.92	0.00	0.00	0.02	1.23	46.73
Key explanatory variables								
ΔLog amount lendable	806,904	-0.02	0.47	-11.39	-0.03	0.00	0.00	12.02
ΔLog amount lent	9,558	-0.05	0.62	-11.84	-0.02	0.00	0.01	11.85
Control variables								
Issuance amount ($ m)	896,417	172.25	277.79	0.80	23.25	61.00	195.00	1,617.08
Weighted avg. life (years)	857,359	4.89	1.92	0.10	3.25	5.01	9.14	29.11
Number of initial ratings	897,599	2.15	0.55	0.00	2.00	2.00	2.00	3.00
Initial rating	895,116	2.56	2.67	1.00	1.00	1.00	3.00	18.00
Median FICO score	384,342	694.07	57.51	0.00	676.00	712.00	732.00	788.00
Geographic HHI	566,963	0.34	0.08	0.17	0.29	0.33	0.37	0.95
Pct. of troubled states	897,599	0.10	0.19	0.00	0.00	0.00	0.13	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 natural logarithm of the amount lendable, (2) the natural logarithm of the amount on loan, and (3) the utilization ratio, on security and deal characteristics. Standard errors are clustered at the deal level.

	Lendable	**On loan**	**Utilization ratio**
	(1)	(2)	(3)
Log issuance amount	0.370	0.062	0.266
	(38.35)	(0.42)	(10.76)
Log weighted avg. life	0.891	1.301	1.046
	(41.03)	(6.38)	(13.24)
Number of initial ratings	0.007	-0.300	0.175
	(0.30)	(-0.91)	(3.68)
Initial rating	-0.091	0.001	-0.103
	(-17.34)	(0.01)	(-9.25)
Median FICO score	0.001	0.002	0.000
	(2.34)	(0.87)	(0.15)
Median FICO score missing	0.735	1.579	0.041
	(2.16)	(0.92)	(0.08)
Geographic HHI	-0.408	-0.120	-1.200
	(-2.32)	(-0.07)	(-2.84)
Geographic HHI missing	0.385	-0.717	-0.166
	(6.63)	(-1.17)	(-1.49)
Pct. of troubled states	0.248	0.456	1.132
	(4.58)	(0.61)	(3.63)
N	802,199	11,863	802,781
R^2	0.265	0.382	0.029

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

The table reports regressions of the next-month change in 90-day delinquency rate on changes in the amount lendable, and controls. In specifications (1)-(2), we collapse the data to 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 specifications (3)-(4), we run regressions on the individual tranche level. Standard errors are clustered around deal type × month in specifications (1)-(2), and around deals in specifications (3)-(4).

	Deal level		**Tranche level**	
	(1)	(2)	(3)	(4)
ΔLog amount lendable	-0.047	-0.038	-0.038	-0.021
	(-4.21)	(-3.44)	(-4.36)	(-2.51)
Log issuance amount	0.010		0.019	-0.001
	(2.29)		(7.32)	(-0.60)
Log weighted avg. life	-0.105		-0.042	-0.024
	(-9.09)		(-6.46)	(-6.48)
Number of initial ratings	-0.019		-0.003	0.004
	(-1.82)		(-0.29)	(0.94)
Initial rating	0.000		0.347	0.000
	(0.10)		(2.71)	(0.49)
Median FICO score	-0.025		-0.001	
	(-5.33)		(-4.60)	
Median FICO score missing (Y/N)	-0.161		-0.984	
	(-5.13)		(-4.61)	
Geo HHI	0.252		0.219	
	(4.44)		(4.17)	
Geo HHI missing (Y/N)	-0.193		-0.128	
	(-4.47)		(-3.66)	
Pct. of troubled states	-0.005		0.067	
	(-0.15)		(2.28)	
Month dummies	Yes	Yes	Yes	Yes
Collateral type × cohort FE	Yes	No	Yes	No
Deal FE	No	Yes	No	Yes
N	165,760	166,973	458,111	458,003
R^2	0.053	0.098	0.057	0.106

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

The table reports regressions of the next-month change in 90-day delinquency rate on changes in the on-loan amount (specifications (1)-(2)) and utilization ratio (the ratio between on-loan and lendable amount, specifications (3)-(4)). In all specifications, the unit of observation is one tranche of a given deal, at a given month. Standard errors are clustered around deals.

	(1)	(2)	(3)	(4)
ΔLog on-loan amount	-0.050	-0.047		
	(-1.71)	(-1.75)		
ΔUtilization ratio			-0.003	-0.007
			(-0.18)	(-0.39)
Log issuance amount	-0.018	-0.009	0.019	-0.067
	(-1.44)	(-0.70)	(7.31)	(-0.62)
Log weighted avg. life	0.044	0.028	-0.043	-2.475
	(0.96)	(0.33)	(-6.56)	(-6.65)
Number of initial ratings	-0.003	0.402	-0.002	0.457
	(-0.16)	(3.97)	(-0.28)	(0.97)
Initial rating	-0.012	-0.003	0.004	0.039
	(-1.34)	(-0.57)	(2.78)	(0.54)
Median FICO score	-0.177		-0.144	
	(-1.27)		(-4.60)	
Median FICO score missing (Y/N)	-1.300		-0.984	
	(-1.29)		(-4.61)	
Geo HHI	0.556		0.220	
	(1.03)		(4.17)	
Geo HHI missing (Y/N)	-0.039		-0.129	
	(-0.30)		(-3.70)	
Pct. of troubled states	-0.074		0.068	
	(-0.63)		(2.31)	
Month dummies	Yes	Yes	Yes	Yes
Collateral type × cohort FE	Yes	No	Yes	No
Deal FE	No	Yes	No	Yes
N	5,145	5,058	458,303	458,194
R^2	0.028	0.046	0.057	0.106

Table V: Robustness

The table presents results the estimates of a number of robustness checks. In all specifications, the dependent variable is a measure of performance, regressed on the log-change in lendable amount and the set of control variables used in Table III, with and without deal fixed effects. All specifications are estimated on tranche-level data, and in all specifications except those in panel B the measure of performance is the change in 90-day delinquency rates. The first row reports the baseline estimates from Table III. Panel A considers predictions over longer horizons (3 and 6 months instead of 1 month). Panel B considers alternative performance measures: changes in foreclosure rates, and changes in cumulative deal losses. Panel C considers alternative sub-samples: early (2002-2005), middle (2006-2008), and late (2009-2010). Panel D considers alternative measures of changes in lendable amount: positive, negative, and as a fraction of the issuance amount.

	OLS			**FE**		
	Coeff.	(t-stat)	N	Coeff.	(t-stat)	N
Baseline	-0.038	(-4.36)	458,111	-0.021	(-2.51)	458,003
A. Longer horizons						
3 months	-0.034	(-3.59)	439,580	-0.020	(-2.23)	439,471
6 months	-0.030	(-3.22)	411,603	-0.020	(-2.21)	411,494
B. Alternative performance measures						
ΔForeclosure rate	-0.014	(-1.76)	450,165	-0.006	(-0.78)	450,104
ΔCumulative deal losses	-0.022	(-8.17)	233,452	-0.014	(-5.97)	233,412
C. Sample period						
2002-2005	-0.036	(-2.05)	20,176	-0.029	(-1.48)	20,128
2006-2008	-0.051	(-4.44)	278,254	-0.017	(-1.56)	278,174
2009-2010	-0.036	(-2.60)	159,681	-0.033	(-2.43)	159,608
D. Alternative measures of changes in lendable						
Only positive changes	-0.013	(-1.17)	458,111	-0.017	(-1.48)	458,003
Only negative changes	-0.060	(-4.43)	458,111	-0.028	(-2.12)	458,003
Standardized by issuance amount	-0.058	(-2.25)	491,204	-0.057	(-2.22)	491,106

Table VI: Changes in Lendable vs. Changes in Holdings

The table presents results for a horse race between changes in the amount lendable and changes in holdings by institutional investors. In all specifications, the dependent variable is the next-quarter change in 90-day delinquency rate, regressed on the log-change in lendable amount (specifications (1) and (4)), the average change in the portfolio weight (specifications (2) and (5)), or both (specifications (3) and (6)). In Panel A, we collapse the data to 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 on the individual tranche level. Standard errors are clustered around deal type × quarter in panel A, and around deals in panel B.

A. Deal level

	ΔDelinquency rate					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog amount lendable	-0.033		-0.040	-0.031		-0.035
	(-4.87)		(-4.68)	(-4.47)		(-4.09)
Avg. Δ portfolio weight		-3.461	-1.949		-3.123	-1.035
		(-3.27)	(-2.07)		(-3.19)	(-1.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Collateral type × cohort FE	Yes	Yes	Yes	No	No	No
Deal FE	No	No	No	Yes	Yes	Yes
N	55,646	29,880	27,272	55,455	29,545	26,946
R^2	0.128	0.259	0.257	0.239	0.462	0.468

B. Tranche level

	ΔDelinquency rate					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog amount lendable	-0.028		-0.028	-0.016		-0.012
	(-5.33)		(-4.79)	(-3.20)		(-2.13)
Avg. Δ portfolio weight		-0.963	-0.460		-0.877	-0.400
		(-2.75)	(-1.44)		(-2.69)	(-1.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Collateral type × cohort FE	Yes	Yes	Yes	No	No	No
Deal FE	No	No	No	Yes	Yes	Yes
N	152,172	90,955	78,249	152,001	90,758	78,049
R^2	0.125	0.254	0.241	0.247	0.465	0.469

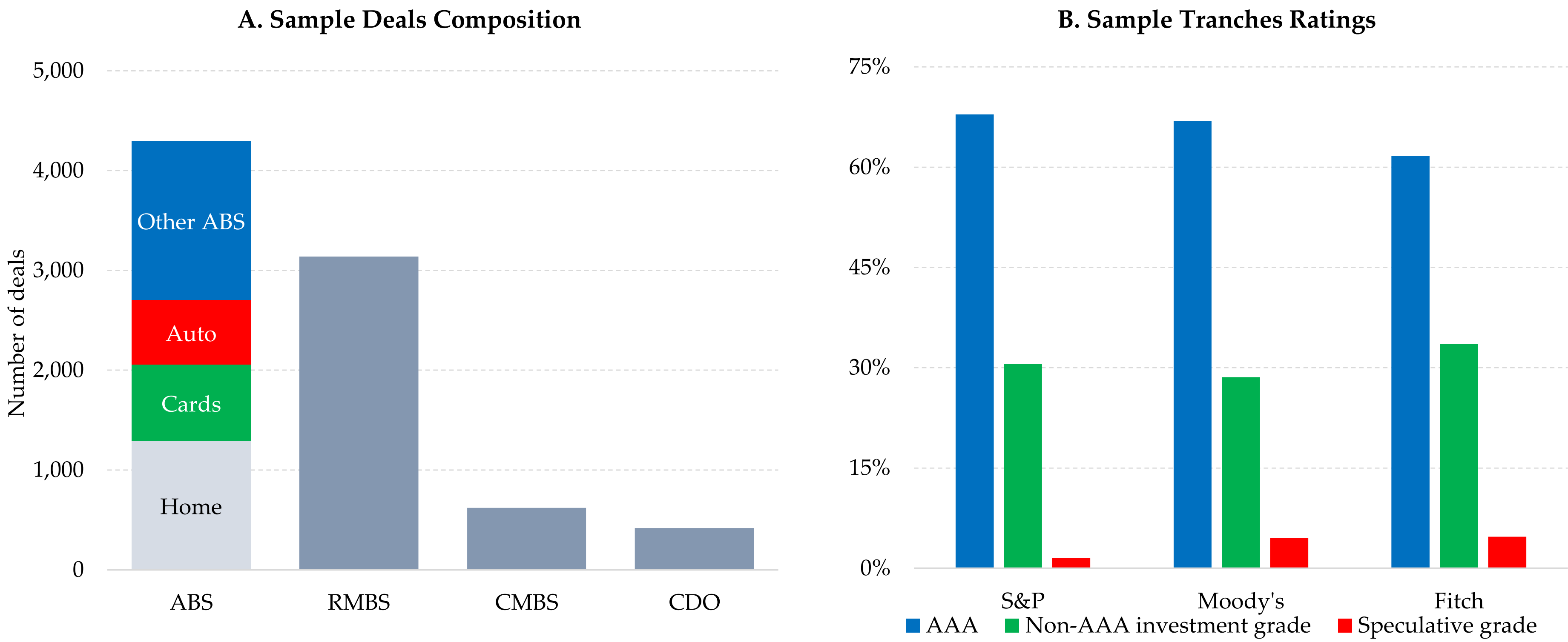

Figure 1 Sample composition

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 initial S&P, Moody's, and Fitch rating.

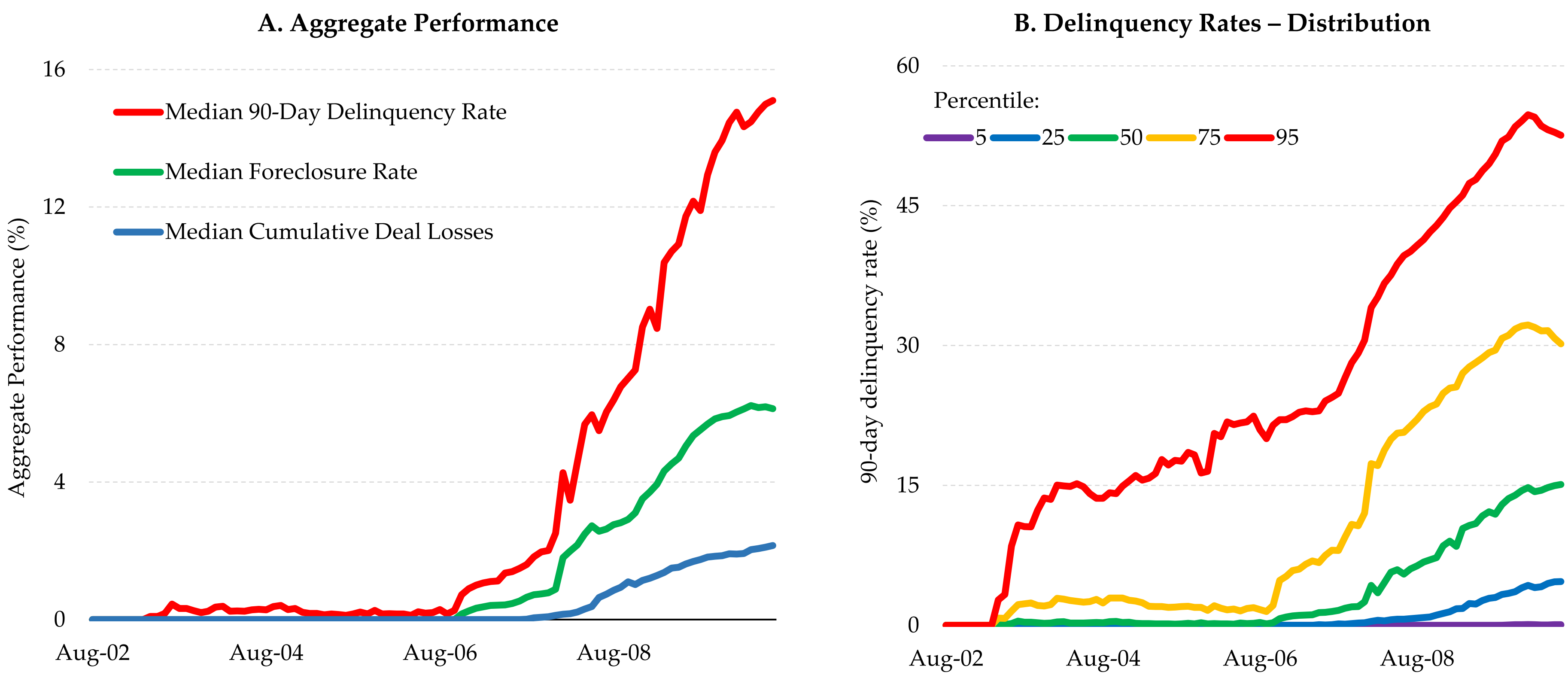

Figure 2 Performance of the sample deals

Panel A plots the aggregate performance of the sample deals, in terms of 90-day delinquency rates, foreclosure rates, and cumulative deal losses. Panel B plots the 5th, 25th, 50th, 75th, and 95th percentiles of the distribution of 90-day delinquency rates over time.

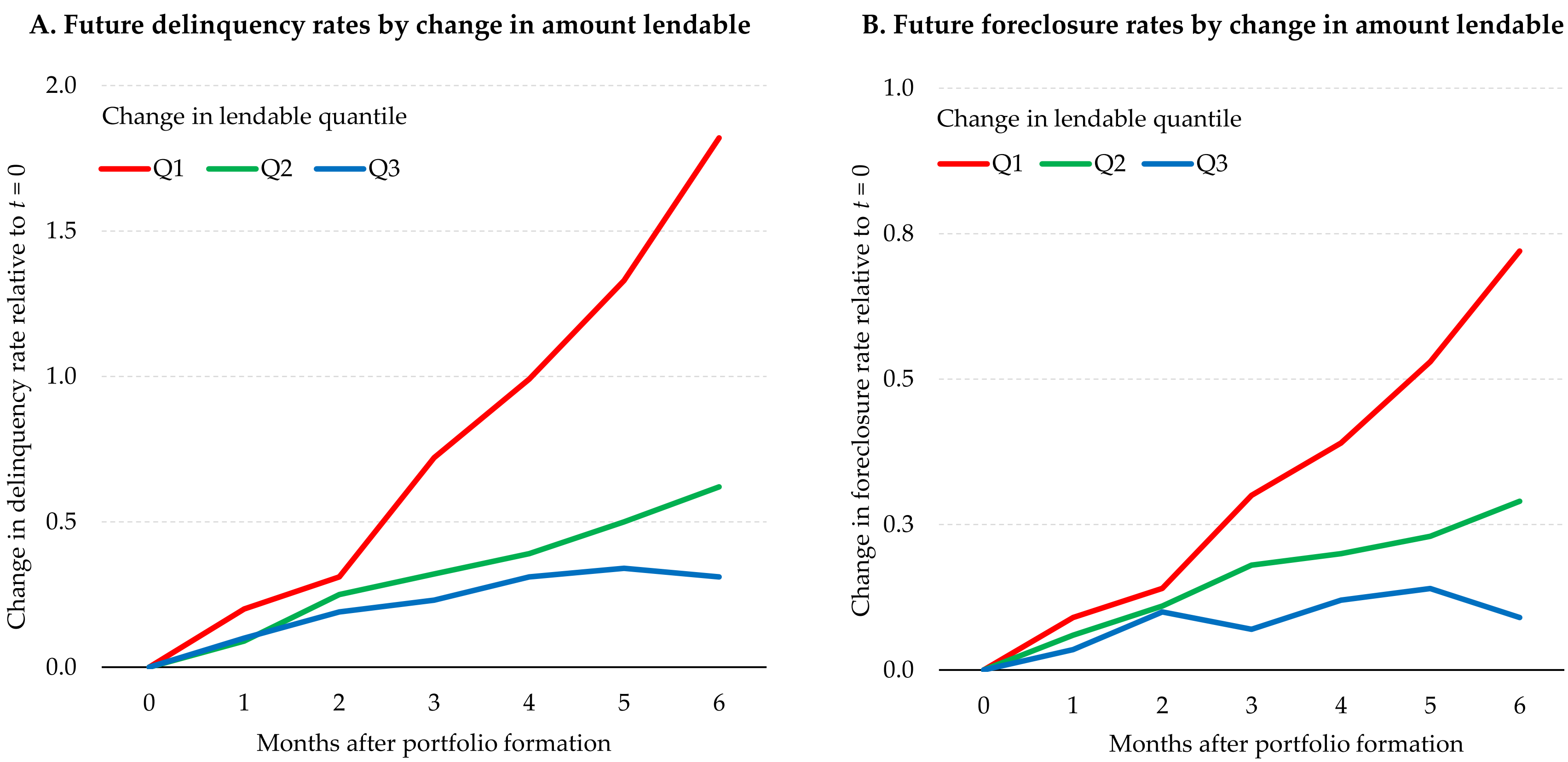

Figure 3 Performance changes following changes in *Lendable*

The graph shows the evolution of delinquency and foreclosure rates in our sample deals, following changes in *Lendable*. Each calendar month, deals are sorted based into quintiles on the change in *Lendable* 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*. 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* are associated with increasing *90-day delinquency rates* (*Foreclosure rates*) over the subsequent 6 months.