Securities Financing and Asset Markets: New Evidence

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Abstract

Using new survey data on bilateral securities funding, we document that broker-dealers move financing rates, collateral haircuts, lending maturities, and position limits together over time and across asset classes. Liquidity of the underlying securities, as opposed to their volatility or credit risk, is the main driver of this behavior, with dealer balance-sheet constraints also playing a role in the funding of less-liquid security types. A simple model of dealer-client interaction rationalizes these findings. Instrumenting with changes in market conventions, we find that funding conditions had little effect on cash securities markets between 2011 and 2019, but the tightening of terms during the COVID-19 crisis likely impaired liquidity and reduced asset returns to some degree.

1 Introduction

The global financial crisis (GFC) of 2007 - 2009 demonstrated the potential importance of securities-financing arrangements between dealers and their clients for market functioning and financial stability. Indeed, Brunnermeier (2009), Gorton and Metrick (2012a), and others argue that these transactions were central to the liquidity spirals and fire sales observed among certain risky assets at the time. The exact size of the market is unclear, but Copeland, Davis, LeSueur, and Martin (2012) estimated dealer-to-client repo (a subset of total dealer-to-client activity) at between \$1 trillion and \$2 trillion as of 2012. The economic importance of these arrangements may be even greater than those numbers suggest, as bilateral repo and margin lending are key channels through which hedge funds and other arbitrageurs obtain leverage, facilitating price discovery and liquidity across a range of securities markets. Several important theoretical papers model collateralized funding to understand both how terms in this market are set and how funding conditions relate to conditions in the market for the securities that are being financed or to broader aspects of financial stability.[1]

Despite the theoretical interest in this market and its evident practical relevance, empirical facts are remarkably hard to come by. Most of what is known about bilateral securities financing, particularly for riskier collateral, is either anecdotal or derives from case studies with uncertain generalizability. For example, while there is broad consensus that financing constraints had important effects on the liquidity and pricing of certain securities during the GFC, there is no systematic evidence on their impact during normal times or in the more-recent market deterioration around the advent of COVID-19. The reason for this gap in the empirical literature is clear: comprehensive data simply do not exist. Adrian, Begalle, Copeland, and Martin (2014) and Baklanova, Copeland, and McCaughrin (2015) discuss the opacity of bilateral securities financing and bemoan the lack of data.

In this paper, we provide new evidence on bilateral dealer-to-client securities financing and its relationship to the respective cash markets for securities by exploiting the Senior Credit Officer Opinion Survey, or "SCOOS." This survey was launched by the Federal Reserve in 2010 precisely out of a recognition that systematic information about this market was lacking. Every quarter, the SCOOS surveys the credit officers responsible for setting

[1]For example, Gromb and Vayanos (2002); Brunnermeier and Pedersen (2009); Geanakoplos (2010); Fostel and Geanakoplos (2014). We discuss the theoretical literature more fully below.

securities-financing terms at the roughly twenty broker-dealers with the largest presence in bilateral securities financing. According to the Fed, these institutions "account for almost all of the dealer financing of dollar-denominated securities to nondealers." The survey asks about the various terms on financing transactions across several different asset classes and client types. It also asks related questions on demand for securities financing, the reasons that dealers are changing their terms, and liquidity in the underlying cash-securities markets. Although the data are public, we are not aware of any previous attempt to use or analyze them in a systematic way.[2]

A simple tabulation of the survey responses reveals that dealers tend to change all types of terms together. The term most frequently adjusted is financing spreads, but, within any asset class, the number of dealers tightening spreads is highly positively correlated with the number tightening haircuts, maturity limits, and credit limits. This suggests that one or more common factors drive all types of financing terms. We present evidence on what those factors are by matching the SCOOS—by quarter and, where possible, by asset class—with a variety of data on market conditions, including financing and trading volumes, asset returns, securities issuance, and various measures of risk and volatility. While many of these variables are correlated to some degree with SCOOS-based indices of financing terms, the factor that emerges as most important is the liquidity of the underlying securities markets. All funding terms across all asset classes display strong unconditional correlations with measures of market liquidity. These correlations survive a variety of controls and specifications, and indeed the inclusion of liquidity largely renders other measures of market conditions, such as volatilities and credit-risk spreads, insignificant in regressions.

We also find evidence that dealer balance-sheet constraints play a role in funding markets. In particular, controlling for other market conditions, we show that dealers tighten financing spreads and haircuts for less-liquid asset classes (consumer ABS, CMBS, and private-label RMBS) when their own equity positions worsen. This suggests a desire to preserve capital and is consistent with mechanisms like those developed in He and Krishnamurthy (2013) and Adrian and Shin (2014). In addition, dealers tend to tighten financing rates (though not other terms) when demand for funding increases. This implies an upward-sloping supply

[2]Eichner and Natalucci (2010) discuss the design of the survey in detail, and Adrian, Covitz, and Liang (2015) explain how the SCOOS might fit into a broader system for monitoring financial stability. The SCOOS is released quarterly at https://www.federalreserve.gov/data/scoos.htm. Our analysis relies only on these aggregate, public data.

curve for funding that is again suggestive of finite dealer balance-sheet capacity.

Although our primary contribution is empirical, we sketch a simple theoretical model, based on Barsky, Bogusz, and Easton (2022), that can rationalize our main results. In the model, dealers require higher spreads in equilibrium to compensate them for a greater risk that balance-sheet constraints will force them to fire-sell repo collateral in an illiquid market. The higher funding spread reduces clients' expected return, pushing security prices down, and, all else equal, these lower prices are consistent with higher haircuts. Thus, haircuts and spreads on funding transactions are positively correlated in the face of fluctuating cash-market liquidity. The model also predicts that reductions in dealers' balance-sheet capacity (i.e., an increased likelihood that they will be forced to sell securities) should cause both spreads and haircuts to tighten, particularly for less-liquid asset classes. This is broadly consistent with our findings on the response of funding terms to dealer equity positions.

As an additional empirical exercise, we ask whether changes in funding terms themselves have explanatory power for market conditions. To do this, we instrument our indies of changes in funding terms using dealers' self-reported frequencies of changing terms to different counterparties because of "market conventions". Because such changes are tied to the implementation of regulations and institutional standards, not quarter-to-quarter market developments, they can safely be taken as exogenous. With these instruments, we find that funding terms typically have little effect on liquidity conditions or on asset returns. However, we do find economically and statistically significant effects in the second quarter of 2020. Models such as Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and Garleanu and Pedersen (2011) imply that funding conditions can be important drivers of asset markets during crises, but those models are nonlinear and there is little evidence on whether their mechanisms are also important under normal circumstances. Our results suggest that, during the relatively quiescent period from 2011 - 2019, funding conditions were largely irrelevant for market conditions. However, during the very stressful period in the first half of 2020 we find that the liquidity and prices of risky assets would not have deteriorated as severely if funding conditions had not tightened, suggesting that arbitrageurs' leverage constraints may hav been binding.

Taken together, our results may help to refine theoretical work on the determinants of funding terms and their relationship to broader market conditions. Existing theoretical papers, such as Gromb and Vayanos (2002), Geanakoplos (2003), Garleanu and Pedersen

(2011), Araujo, Kubler, and Schommer (2012) differ in their implications—or, on some cases, have ambiguous implications—for the volatility and comovement of funding terms. Simple versions of the Geanakoplos model, for example, imply haircuts that fully offset asset risk and constant, zero financing spreads, in contrast to our findings. Moreover, market liquidity, which we find to be the most important determinant of funding terms, is not a concept that typically appears in theoretical papers that model collateralized borrowing contracts. The theoretical framework we develop suggests one possible way of incorporating this idea. We discuss more fully how our results might inform theoretical work in this area in Section 2.1.

As noted above, the primary motivation for our study is the lack of empirical evidence on these questions. Indeed, only two other empirical papers, Auh and Landoni (2016) and Baklanova, Caglio, Cipriani, and Copeland (2019), have studied the bilateral repo market in any detail. While the confidential micro data used in those studies allowed for a number of interesting tests that the SCOOS data do not, their coverage was relatively narrow. A few other papers have examined related markets. Gorton and Metrick (2012a) documented data on inter-dealer financing terms for many different asset classes using data obtained from one dealer at the height of the GFC. And the tri-party repo market, where data on haircuts, rates, and volumes there are more readily available, has been studied relatively throughly (Bartolini, Hilton, Sundaresan, and Tonetti, 2011; Copeland, Martin, and Walker, 2014; Krishnamurthy, Nagel, and Orlav, 2014; Hu, Pan, and Wang, 2018). Importantly, however, the inter-dealer, tri-party, and bilateral repo markets are quite distinct. Our paper is complementary to these previous studies, but it focuses on the bilateral financing of risky collateral between dealers and clients. We take a broad view of this market by covering a variety of asset classes over a ten-year post-GFC period, with data drawn from the dealers that represent the bulk of the market. We are also the first to explore the empirical links between bilateral securities financing activity and other market conditions, including liquidity and returns in the securities markets themselves.[3] We discuss more fully how our results relate to existing empirical work in Section 2.2.

The remainder of the paper is organized as follows. Section 2 places our study in the context of the literature on collateralized funding. Section 3 describes the SCOOS, the main

[3]Fontaine and Garcia (2012) show that liquidity in the cash market for Treasuries is associated with several different measures of "funding conditions," although they do not have direct data on bilateral repo activity.

data we pull from it, and the matched data that we obtain from other sources. Section 4 presents summary statistics for these data, including raw correlations of SCOOS terms with various measures of market conditions. Section 5 runs regressions to examine how terms are determined. Section 6 presents a simple theoretical model that is consistent with our main results. Section 7 presents our analysis of how funding terms affect market liquidity and asset returns. Section 8 concludes. An internet appendix contains additional information and several robustness checks of our main regressions.

2 Relationship to Literature

2.1 Theory

A sizable theoretical literature has emerged studying how the terms on collateralized lending are determined and how they relate to conditions in the underlying asset markets. The empirical results we present below have the potential to inform this literature in a number of ways. Here, we briefly review this literature and note a few places where our results speak to existing models.

Some papers simply take as given the margins that apply to financial assets (Gromb and Vayanos, 2002; Garleanu and Pedersen, 2011). Financing spreads in these models then adjust to ensure that lenders are fully compensated for risk.[4] Instead, our paper studies empirically how these and other funding terms vary and are determined by market conditions across asset classes and over time. A relatively straightforward approach to obtaining variation in margins in theoretical models is to assume that financial intermediaries operate with an exogenous value-at-risk (VaR) constraint (e.g., Brunnermeier and Pedersen, 2009; Aymanns and Farmer, 2015). In these cases, the VaR parameter pins down haircuts, given a level of asset volatility, and thus pre-determines their importance relative to spreads in adjusting to market conditions. While these models capture key aspects of collateralized lending, the assumption that lenders take the VaR constraint as given is strong and effectively imposes that uncertainty about asset payoffs is the only determinant of funding terms. That is

[4] For our purposes "margins" and "haircuts" are synonyms; they are the inverse of client leverage. "Financing spreads" are the difference between the interest rates that dealers charge clients on loans and their own cost of collateralized borrowing (often taken to be the risk-free rate).

inconsistent with our empirical results, which suggest market liquidity and dealer balance-sheet constraints are of at least as much importance.

Genakoplos (2003; 2010) and Fostel and Geanakoplos (2008, 2014, 2015) have studied the endogenous determination of funding terms and asset prices in models with binomial payoff structures and a continuum of agent beliefs about state probabilities. In such models, lenders and borrowers generally agree to set haircuts to cover worst-case scenarios—sometimes referred to as a "zero-VaR" or "no-default" equilibrium. (Some other papers, such as Gromb and Vayanos, 2002, simply start from the premise that lenders always set a zero VaR.) Since there is no chance that the lender experiences losses in such a situation, financing spreads are always zero. Our empirical results cannot be reconciled with this type of model either, since we find financing spreads change at least as often as haircuts do and are at least as highly correlated with market conditions.[5]

There are a few options for altering models of collateral equilibrium to obtain endogenous variation in both spreads and haircuts. One is to suppose that the assets being borrowed against have non-pecuniary benefits (see Geanakoplos, 2010 and Cipriani, Fostel, and Houser, 2019). However, while this case may be realistic for some types of collateralized lending, like housing, it does not apply to securities financing. Another possibility is to suppose that collateral is scarce relative to the desired amount of borrowing. Araujo, Kubler, and Schommer (2012) show how contracts involving default (and non-zero financing spreads) may be traded in this case. Finally, one can move away from binomial environments. Geanakoplos (2003, 2010) for example, provides examples in which financing spreads can be non-zero in models with three state outcomes. Simsek (2013) produces results of a similar flavor in a model with a continuum of possible asset payoffs but a finite number of investor types; this is the approach we follow in Section 6.

In the papers mentioned so far, uncertainty and disagreement about asset payoffs are typically the primary determinants of terms.[6] We find that measures of market uncertainty and volatility are indeed unconditionally correlated with our indices of changes in financing

[5]In a related partial-equilibrium setting, Acharya, Gale, and Yorulmazer (2011) show how a borrower's debt capacity can switch to a no-default contract when bad news arrives. A "market freeze" in their model thus generally involves haircuts moving higher and financing rates moving from positive to zero; such negative comovement is the opposite of what we find in the data, even during the most stressful periods.

[6]The distribution of wealth across investors with different beliefs or risk tolerance also matter, although this is not something we are able to observe well in the data.

terms. However, in regressions, measures of trading liquidity are more economically and statistically significant than measures of volatility or risk. "Liquidity" is not a concept that typically enters into the literature above, and of course its precise meaning is somewhat difficult to pin down.[7] Garleanu and Pedersen (2007) show how concerns about market liquidity—meaning, the ease of trading an asset—can affect VaR calculations by increasing the expected length of time that it will take to sell a security, and they cite anecdotal evidence that this is how dealers view the problem. Their model concerns market-making activity, but it is easy to see how an analogous dynamic ought to apply to securities financing. Duffie and Ziegler (2003) and Brevas (2006) make a similar point.

We also find evidence that funding terms relate to the condition of dealers themselves. This is another dimension that is generally absent from the theoretical papers noted above, but a related literature addresses these issues. In Adrian and Shin (2014), intermediaries dynamically change their VaR thresholds to maintain constant probabilities of bankruptcy. Effectively, this means loosening terms on lending to expand their balance sheets when their own leverage declines. This is consistent with our findings with respect to dealer equity.[8]. Oehmke (2014) shows how haircuts can adjust to compensate dealers both for their balance-sheet constraints and market illiquidity. His model is broadly consistent with our results, although it takes several important aspects of the problem (including the asset price) as exogenous. In contrast, our model of Section 6 endogenizes the price, but it is silent on the sources of liquidity and balance-sheet shocks.

We also test whether market liquidity and pricing are respond when dealers change funding terms. These results speak to models such as Gromb and Vayanos (2002), Garleanu and Pedersen (2011), and Vayanos and Wang (2013), which explain market liquidity through funding constraints. Brunnermeier and Pedersen (2009) effectively link the potential two-way causality between funding terms and market liquidity, showing how this sort of dynamic can result in an adverse feedback loop. Again, "liquidity" can mean somewhat different things in these models, but it typically involves a temporary deviation of a security's price from its fundamental value. Importantly, these models are generally nonlinear. For example,

[7]Fostel and Geanakoplos (2008) discuss a notion of an asset's liquidity in collateral equilibrium, but they define it as borrowing capacity—that is, they essentially equate it with the asset's haircut by construction.

[8]Of course, managing the VaR of a dealer's balance sheet as a whole is a different problem from managing the VaR for a particular funding position; the model in Adrian and Shin (2014) thus does not provide guidance on differential changes in funding terms across asset classes like those we find.

in Garleanu and Pedersen (2011), during good times, when leverage constraints are not binding, prices fully reflect fundamentals (one definition of "liquidity"). But they deviate from fundamentals during bad times as arbitrageurs do not have sufficient borrowing capacity to fully intermediate markets. Broadly speaking, this is consistent with our findings.

Finally, our empirical results demonstrate that dealers significantly change other terms on securities financing—in particular, maximum maturities and maximum amounts— over time and in a way that resembles how they change financing spreads and haircuts. These are not aspects of collateralized lending that are addressed at any length in the theoretical literature to date.[9] In the interests of parsimony, our theoretical model also sidesteps consideration of these other dimensions of the problem. However, incorporating them could be a productive direction for future work.

2.2 Evidence

Because of the lack of data, there is little empirical evidence from the bilateral funding market that can speak to most of the theoretical questions noted above. A few papers address related questions using limited samples. Gorton and Metrick (2012a) show that both haircuts and financing rates moved higher during the GFC but that haircuts moved much more. However, their data were for interdealer transactions, not dealer-client transactions.[10] Auh and Landoni (2016) use micro data to show that clients may face a choice of different haircut-financing rate pairs for particular collateral at any point in time, but these data came from a single asset manager during the pre-GFC period, and most of the transactions financed mortgage-backed CDO securities. Baklanova, Caglio, Cipriani, and Copeland (2019) use data provided from several banks to document the patterns of terms across asset classes, though these data cover only a single calendar quarter and primarily reflect inter-dealer lending, securities-borrowing activity, and transactions backed by Treasury securities. Our data exclude inter-dealer financing and dealer demand for securities borrowing, as well as

[9] In the binomial models of Geanakoplos (2010) and He and Xiong (2012), equilibrium lending contracts always have the shortest possible maturity. However, these papers are about the terms on contracts that are actually traded, whereas our data provides information on maturity *limits*, which may not be binding in equilibrium. We are not aware of papers that model this kind of maturity rationing or link it to market conditions.

[10] The distinction between the inter-dealer and dealer-to-client markets is potentially important because dealers are often only intermediaries in securities financing, not end users, and because one would expect that the nature of relationships and counterparty risk differ between dealer-dealer and dealer-client interactions.

transactions secured by Treasuries. We thus isolate the financing of risky collateral, which is the type of lending addressed by most of the theoretical papers discussed above.

A 2010 study published by the Committee on the Global Financial System (CGFS, 2010) reported the results of interviews with participants in the bilateral funding market. That study noted several different methodologies for how terms were set. (The study focused primarily on the setting of haircuts.) However, respondents frequently emphasized the importance of market liquidity, which is consistent with our main findings below. Interviewees also often indicated that credit limits were the first margin of adjustment to be used in times of market stress. We also provide additional evidence on the behavior of such limits.

Another type of evidence comes from controlled experiments. Cipriani, Fostel, and Houser (2018) study collateralized funding in a laboratory setting and confirm that assets with higher collateral value trade at higher prices. Cipriani, Fostel, and Houser (2019) show that when leverage is allowed to be endogenously determined in such a setting (i.e., participants can contract on haircuts) an outcome resembling a no-default equilibrium emerges for financial assets.

The introduction noted several papers that study the tri-party repo market. Given that dealers participate heavily in both the tri-party and bilateral markets, one might expect them to be closely linked. Yet there are important institutional differences between the two markets that generate significant segmentation and potentially lead to significant differences in their behavior. For example, dealers are primarily borrowers tri-party repo, and the lenders are typically money-market funds and other cash investors. In the bilateral market, in contrast, dealers are the lenders, and the borrowers are hedge funds, asset managers, and other "buy side" market participants. Consistent with segmentation between the two markets, Krishnamurthy, Nagel, and Orlav (2014) and Copeland, Martin, and Walker (2014) show that tri-party haircuts were largely unchanged during the GFC, even as anecdotal accounts (and the Gorton and Metrick, 2012a evidence) suggested significant tightening in bilateral repo.[11] Our data are also consistent with substantial differences between these two markets (although we do not focus on the comparison in this paper), as we find very weak correlations between the tri-party data and the SCOOS data.[12]

[11]In their study of the tri-party market, Copeland, Martin, and Walker (2014) also briefly discussed some confidential data on bilateral-repo haircuts collected by the Federal Reserve Bank of New York, but that was not the focus of their paper.

[12]Martin, Skeie, and von Thadden (2014) provide a theoretical framework that rationalizes some of the

3 Data

3.1 The SCOOS

In recognition of the lack of data on bilateral securities financing relative to its potential importance, the Federal Reserve launched the Senior Credit Officer Opinion Survey in the second quarter of 2010. The survey design is described in Eichner and Natalucci (2010). A revision that added some questions to the survey took place in Q3 2011, so a few of our data series begin only on that date. Our sample ends in Q2 2020. In addition to securities financing, the SCOOS covers several other topics having to do with dealer-client interactions. In particular, a large section of the survey asks about aspects of the market for over-the-counter derivatives. We largely ignore this other information for the purposes of this paper.

The SCOOS is administered quarterly to the senior credit officers at "the financial institutions that account for almost all of the dealer financing of dollar-denominated securities to nondealers and that are the most active intermediaries in OTC derivatives markets." Senior credit officers are responsible for allocating financing to a dealer's clients, and for setting the terms on that financing, so they are the individuals best positioned to provide information on funding conditions. Over our sample period the number of senior credit officers polled in the survey ranged from 20 to 23. Nearly all of the institutions covered were "primary dealers"—the large banks that are the Fed's counterparties in open-market operations. Thus, for some purposes, we will match available information about the primary dealers with the SCOOS data under the assumption that it reflects information about largely the same set of entities.[13]

The main survey questions of interest for us have to do with securities financing. The SCOOS defines this activity as "lending to clients collateralized by securities." It goes on to

differences between the tri-party and bilateral repo markets, particularly during the GFC. Anbil, Anderson, and Senyuz (2021) document such segmentations in the Treasury repo market during the stressful period of September 2019. Dealers also finance their own securities inventories through tri-party repo. In an interesting complement to our results, Macchiavelli and Zhou (2022) show that this creates a significant link between tri-party funding conditions and the provision of market liquidity at the dealer level.

[13]Primary dealers include the largest broker-dealers operating in the United States. One requirement of primary dealers is that they "provide insight into developments in the markets in which they transact with the New York Fed, on an ongoing basis." Over our sample, the number of primary dealers ranged from 18 to 22. The remaining SCOOS respondents are other financial institutions that, though not primary dealers, have a large presence in the securities-financing or OTC derivatives market.

explain that "such activities may be conducted on a 'repo' desk, on a trading desk engaged in facilitation for institutional clients and/or proprietary transactions, on a funding desk, or on a prime brokerage platform." Thus, the SCOOS takes a broad, institution-wide view of the bilateral funding market. Importantly, however, the definition used here excludes securities-borrowing activity (i.e., situations in which dealers source specific securities to facilitate short selling or delivery), and it excludes financing arrangements with other dealers.

Most of the questions we use are asked individually for each of seven different asset classes (i.e., collateral types): agency mortgage-backed securities, high-yield corporate bonds, equities, high-grade corporate bonds, commercial mortgage-backed securities, consumer asset-backed securities, and non-agency residential MBS. (The questions on the last four categories begin only after the 2011 survey revision.) In each case, respondents are asked to consider only dollar-denominated instruments. The most important questions for us are those that have to do with changes in financing terms. The SCOOS asks specifically about four different types of terms, for each asset class: financing spreads, haircuts, maximum maturities, and maximum amounts (i.e., credit limits). It also asks separately about the terms offered to "average" clients and to clients who are "most favored ... as a consequence of breadth, duration, and/or extent of relationship."

A representative question on terms is the following:[14]

> *Over the past three months, how have the terms under which agency RMBS are funded changed?*
>
> *Terms for average clients:*
>
> *Haircuts:*
>
> __ *Increased considerably*
> __ *Increased somewhat*
> __ *Remained basically unchanged*
> __ *Decreased somewhat*
> __ *Decreased considerably*

The SCOOS questions were modeled after those in the Senior Loan Officer Opinion

[14]The use of the passive voice in this question is not meant to indicate that the respondents should assess the direction of terms in the market as a whole. In the introduction to this section of the survey, the instructions specifically note that the questions are about "securities funding at your institution."

Survey (SLOOS), which the Federal Reserve has conducted since the 1960s. In both surveys most questions have the sort of qualitative format shown above. There are some obvious drawbacks to dealing with data of this nature—for example, economic significance would be much easier to assess if changes in haircuts were simply expressed in percentage points. Our data cannot precisely speak to questions about the average levels of spreads or haircuts or other terms in funding markets, only to the number of dealers who report changing these terms in each quarter. Moreover, the qualitative nature of the questions introduces an element of subjectivity—one dealer's threshold for "increased somewhat" versus " increased substantially" may be different from another's. And, we have no way of no way of mapping numbers of dealers into the changes in terms facing the average or marginal borrower in funding markets. Although dealers who do not materially participate in a given funding market do not respond to questions concerning that market, the data come to us otherwise unweighted by transaction volumes.

That said, there are some advantages to the qualitative responses. First, they allow us to draw on the established empirical literature that has adapted to this sort of data in the SLOOS and found it useful.[15] Second, although most of the financing terms could have been quantified in principle, other variables that the SCOOS asks about, such as liquidity and funding demand, are multifaceted and somewhat vaguely defined. In these cases, precise quantitative measurement might not be possible or even desirable. More importantly, despite their imperfect format, the SCOOS data give us a window into an otherwise opaque segment of financial intermediation, and they do so in a way that covers effectively the entire market and allows for measurement consistency across asset classes and over time.

In any case, we take the SCOOS data as given and, following previous work using the SLOOS, we create diffusion indices for each type of term in each asset class in each quarter:

$$\tau_{i,j,t} = \frac{\#_{\mathrm{t}} \text{ tightening term } i_j - \#_{\mathrm{t}} \text{ easing term } i_j}{\text{total respondents}_{jt}} \tag{1}$$

where i indexes the four types of terms asked about in the SCOOS (spreads, haircuts, maximum maturities, and maximum amounts), j indexes asset class, and t indexes calendar quarters. The total number of respondents is indexed by j because a few dealers do not finance certain types of securities at all and thus do not respond to questions about those

[15] E.g., Lown and Morgan (2006); Ivashina and Scharfstein (2010); Gilchrist and Zakrajsek (2012).

asset classes. Note that the indices are signed such that positive values always indicate tighter terms. We also constructed weighted indices, giving a response like "tightened considerably" twice as much weight as "tightened somewhat." However, as we show below, there was very little difference in results between the weighted and unweighted indices. We therefore use the unweighted series in most of our analysis for ease of interpretation.

The SCOOS also asks about demand for securities financing and cash-market liquidity for each of the asset classes. Sample questions of each type are as follows:

> *Over the past three months, how has demand for funding of agency RMBS by your institution's clients changed?*
>
> __ *Increased considerably*
> __ *Increased somewhat*
> __ *Remained basically unchanged*
> __ *Decreased somewhat*
> __ *Decreased considerably*

> *Over the past three months, how have liquidity and functioning in the agency RMBS market changed?*
>
> __ *Improved considerably*
> __ *Improved somewhat*
> __ *Remained basically unchanged*
> __ *Deteriorated somewhat*
> __ *Deteriorated considerably*

We collect the responses to each of the financing-demand and market-liquidity questions and create diffusion indices in the same manner that we do for the terms questions. In particular, we denote by $\lambda_{j,t}$ the net fraction of dealers reporting that liquidity and functioning improved for asset class j over quarter t. We note that, unlike the other SCOOS questions used here, the "liquidity and functioning" question does not refer to the securities-financing market, but rather to the cash market for the underlying collateral. Indeed, respondents are specifically instructed to take account of a broad set of indicators of that market, and not just financing conditions themselves, when answering this question. That will be important for us later, because we will use the responses to this question as our primary measure of market liquidity. The liquidity question is not asked for the equity market, presumably because equities are exchange-traded and do not face potential illiquidity in the same sense that OTC-traded instruments do.

Finally, in a separate section, the SCOOS asks dealers about the reasons that they tightened or eased their terms in each quarter. These questions do not align directly with the terms questions discussed above, for several reasons. Nevertheless, we exploit these data in our analysis in Section 7. We defer the discussion of the details of these questions until then.

3.2 Other data

We match the SCOOS data by date and asset class to a variety of potentially relevant data from other sources. First, we collect data on aggregate security returns. The particular indices we use to measure returns are listed in Table 1. Each edition of the SCOOS reports the dates during which it was conducted (typically, the last or second-to-last week of the second month of each calendar quarter), and all of its questions refer to changes in conditions over the preceding three months. We calculate the return on each index between the same sets of dates. The price indices also allow us to calculate asset-class-specific measures of realized volatility. Specifically, we do this by computing the standard deviation of daily changes in index levels during the month that ends on the SCOOS reporting date. We then difference these series across quarters to obtain a measure of the change in volatility for each asset class that approximately lines up with the timing of the changes in conditions reported in the SCOOS.

A second source of asset-specific information we use is the FR-2004 report produced weekly by the Federal Reserve Bank of New York. This report collects information on the aggregate value of securities that primary dealers receive through operations other than outright purchases ("securities in"), a category that includes bilateral securities financing. As noted above, the SCOOS respondent panel closely matches the set of primary dealers. Since the SCOOS asks about quarterly changes, we compute the percentage differences in the FR-2004 quantities, matched as nearly as possible to SCOOS reporting weeks, relative to three months prior. The FR-2004 also reports the amount of fails-to-deliver in repo transactions and the volumes of secondary-market trading conducted through the primary dealers. Again, they are reported weekly for different asset types (though not for every asset type in every period), and we do the matching to the SCOOS data in the same way as above. To adjust for changes in the amount of financing, we calculate the ratio of the value of fails-to-deliver to the amount of financing occurring that week. We note that the FR-2004 data do not exist separately for every asset class covered by the SCOOS (and the set of asset classes reported changes over time). We therefore must drop some observations when using these data.

To further connect SCOOS responses to activity in asset markets, we use data from SIFMA to match SCOOS responses with quarterly asset-specific gross issuance amounts and (within quarter) percentage changes in monthly trading volumes for structured finance and corporate debt assets. For equities, we take issuance and trading volume data from the Financial Accounts of the United States and the NYSE.[16] For corporate bonds we also construct Amihud (2002) liquidity statistics from a large sample of transactions in TRACE. The paucity of trade data prevent us from calculating these measures for other asset classes.

Since previous work has emphasized differences between the bilteral and tri-party repo markets (Copeland et al., 2014; Krishnamurthy et al., 2014), we investigate these differences further by matching our survey responses to the New York Fed's publicly available tri-party repo data. These data track volumes, market concentration, and percentiles of the distribution of haircut values in the tri-party repo market for each of the asset classes we consider except CMBS, starting in the third quarter of 2010.

We calculate several aggregate measures of dealer health. First, we use the Financial Accounts to compute percentage changes in dealer equity levels and changes in the fraction of liquid assets at securities broker-dealers. Second, using the same data source, we follow Adrian, Etula, and Muir (2014) and compute quarterly percentage changes in (book value) dealer leverage. Third, we compute the average credit default swap spread of the primary dealers, using data from Bloomberg, and we take the ratio to the investment-grade CDX index to obtain a dealer "excess" CDS spread. We compute the first differences of these series across SCOOS reporting dates.

Finally, we make use of a variety of other sources of time-series data. To measure changes

[16]The Financial Accounts data are reported as of quarter-end. We interpolate to obtain measures that line up with the SCOOS reporting dates.

in the macroeconomic outlook, we collect quarterly revisions to the one-year-ahead mean GDP forecast from the Survey of Professional Forecasters (available from the Federal Reserve Bank of Philadelphia).To measure market perceptions of risk and risk aversion, we collect the VIX index of stock-market implied volatility, the MOVE index of Treasury-market volatility, and the swaption-implied volatility of one- and ten-year swaps. To capture broad changes in interest rates, we use 3-month and 10-year Treasury yields. As additional measures of broad financial market conditions, we collect the TED spread, the spread between on- and off-the-run five-year Treasury yields, the Gilchrist-Zakrajsek (2012) excess bond premium, the investment-grade and high-yield non-financial CDX indices, and the Chicago Fed Financial Conditions Index. As above, we difference (or log-difference) all of these series by quarter, matching as closely as possible to the SCOOS reporting dates.

4 Stylized facts about securities financing

4.1 Funding terms

Table 2 reports summary statistics for various measures of the aggregate changes in securities-financing terms, as measured by the SCOOS. We compute these statistics separately for average clients and "most favored" clients, and for the unweighted and weighted diffusion indices discussed above. Regardless of how they are measured, the average number of dealers changing their funding terms is essentially zero, when computed over the full sample. This implies that there is no secular trend toward tightness or looseness. In addition, terms typically are fairly stable. Only 19% of dealers change their financing spreads in either direction in an average quarter, while even fewer change their other terms. Even so, the changes in the other terms are not zero. Maximum maturities move the least, but still about 10% of dealers per quarter change them. Haircuts change less frequently than financing spreads, but more frequently than maximum maturities or maximum amounts. It is also apparent from the table that the choice of weighted versus unweighted index does not matter much. Weighted indices are a bit more volatile, but, as shown in the bottom panel of the table, they are almost perfectly correlated with the unweighted indices. Since they appear to behave in very similar ways, we use the unweighted index in the remainder of the paper for ease of interpretation.[17] Similarly, perhaps surprisingly, favored clients' terms are nearly as volatile as and highly correlated with those of average clients. Consequently, we ignore this distinction for the remainder of the analysis and simply report results averaging across the indices for the two client types.

Table 3 breaks out the volatility of funding terms by asset class. The basic patterns just described hold across most asset classes—although none of the terms change very often, across most asset classes dealers change financing rates a bit more frequently than other terms, and maximum maturities and amounts a bit less often. Terms are generally most variable for private structured products, and they are least variable for agency MBS and equities.

Figure 2 plots two views of the data. In panel A, we plot the indices for each of the four terms, averaging across all asset classes in each quarter. In panel B, we plot the indices for each of the seven asset classes, averaging across all term types. As measured by our indices, terms generally eased during the first year of the SCOOS's existence, as markets continued to recover from the GFC. They tightened sharply in the second half of 2011, around the time of the downgrade of U.S. credit rating and the onset of the European sovereign debt crisis. Then, after a period of relative stability, terms tightened again in 2015 and 2016. This episode was associated with a number of stressful market events, including a sharp selloff in Chinese stocks, a collapse of oil prices, and the U.K.'s "brexit" vote. Dealers eased terms a bit, on net, over the period 2017 to 2019, as markets generally performed well. Finally, and most dramatically, the majority of dealers reported tightening terms across the board in the last quarter of our sample, reflecting the retreat from risk taking that occurred with the onset of the COVID-19 crisis.[18]

Stepping back, we note two general properties of these graphs. First, although the brief narrative we have just given emphasized the common movements in the indices, there is also a substantial amount of dispersion across term types and asset classes. This means that there are potentially interesting phenomena to explain in the cross-sectional dimensions

[17]We reproduced our main results using the weighted index with no material differences.

[18]The Q1 and Q2 2020 surveys were conducted in late February and early May, respectively, and thus skipped over the most acute financial-market stress that occurred in late March and early April. Still, the large movements in the last quarter of the sample raise the concern that our results could be driven by this one extreme observation. We show below that omitting this quarter from the analysis does not change the basic statistical and economic significance patterns in the data.

of the data. Second, there is very little serial correlation in the series. We would expect this, since the SCOOS asks about *changes* in terms each quarter. It implies that spurious correlation between SCOOS series and other data is unlikely to be a problem.

Table 4 shows how our indices of changes in terms are correlated with each other and with other market data. In panel A, we pool across all asset classes for each type of term. In panel B, we pool across all terms for each asset class. Shaded columns indicate data on which we have only time-series observations, while all other columns are matched both by time and by asset class.

The first four columns of Panel A show how terms correlate with each other. As was evident from Figure 2, dealers tend to change all terms together in the same direction. It is particularly noteworthy, in light of previous empirical work, that the fractions of dealers changing financing rates and changing haircuts have a correlation of over 80%.[19] In Internet Appendix Table A1, we decompose these correlations into their cross-sectional (between-asset-class) and time-series (within-asset-class) components and show that they are strong in both dimensions. This motivates our search for common factors driving funding-market tightness. On the other hand, the correlations between the terms indices are not perfect, and another question will be whether there are identifiable factors that affect different terms differently.

Columns [5] through [8] show how SCOOS terms indices correlate with measures of securities-market liquidity. These correlations are quite high, both for the liquidity indicators that are matched by asset class and for the time-series data. They hold across all four terms and (where the measurement is possible) across all seven asset classes. The next four columns show correlations between the terms indices and measures of volatility. The correlations with realized volatility, are positive but modest and are largely driven by corporate bonds.[20] The correlations with equity *implied* volatility are somewhat stronger, while correlations with implied interest-rate volatility are mostly insignificant. The fractions of dealers changing terms also have a modestly negative unconditional relationship with asset returns, though

[19]Within the portfolio of securities that they examine, Auh and Landoni (2016) find that transactions with higher rates have lower haircuts, and Baklanova et al. (2019) find a similar result for U.S. Treasury securities. Our results are not directly comparable, because they are with respect to different asset classes over time, rather than for particular collateral at a point in time. Still, the correlations suggests that spreads, haircuts, and the other terms generally move together in the aggregate.

[20]Our measure of realized volatility is backward-looking. Following Gorton and Metrick (2012a), we also tried using *future* realized volatility but found little relationship with terms.

this is almost entirely due to the corporate bond and equity categories. They have little overall correlation with trading volumes, though they do show a negative relationship with issuance for some of the less-liquid asset classes. Our indices of changes in terms are very highly correlated with revisions in GDP forecasts, reflecting their sensitivity to the business cycle.

Our indices of funding demand (column [17]) are negatively correlated with our indices of funding terms in some cases and positively correlated in others. Meanwhile, we find moderate negative correlations between the fraction of dealers changing terms and the securities-financing volumes reported in the FR-2004, suggesting that, on net, tighter terms tend to reduce the volume of securities financing that takes place. Correlations of financing volumes with SCOOS-reported demand (not shown in the table) are somewhat stronger.[21] Perhaps surprisingly, the correlations of our SCOOS-based terms indices with measures of activity in the tri-party market are near zero on average. This again highlights the fact that these markets can behave much differently.

The next set of columns contains correlations with measures of dealer condition. These correlations all point to a negative relationship between the health of dealers and the tightness of terms—wider excess CDS spreads, higher leverage, and decreases in equity levels are all associated with tighter reported funding conditions. Dealers also increase their holdings of liquid asset during quarters when they tighten their terms.

Finally, the last several columns show the correlation of financing terms with other measures of broad market conditions. More dealers tighten terms in environments with higher credit risk, as measured by the CDX indices, and with the Gilchrist-Zakrajzek (2012) excess bond premium, which is often interpreted as a measure of investor risk-bearing capacity. Our terms indices have a fairly strong negative correlation with the Chicago Fed Financial Conditions Index, which is not surprising given that that index subsumes many of the other measures of financial conditions just mentioned. They also have a pronounced negative association with interest rates (higher rates are associated with easier terms), presumably

[21] One reason the correlations between terms and securities-financing volumes are not stronger may be that the FR-2004 data include certain types of funding activity that the SCOOS excludes. In particular, they include securities borrowing and transactions with other dealers. Evidence in Gorton and Metrick (2012b) and Baklanova et al. (2017) suggests that these two categories in fact constitute the majority of dealer activity. After 2015, the FR-2004 breaks out repo volumes from other types of securities-financing contracts for certain asset classes, but the mingling of interdealer and client financing remains.

reflecting comovement over the business cycle.[22]

4.2 Liquidity

The simple correlations above already suggest a close link between market liquidity and funding terms, and our tests below will confirm this connection more carefully. Our preferred measure of liquidity in this paper is the survey-based measure provided by the SCOOS itself—the net fraction of dealers reporting improving or deteriorating "liquidity and functioning" conditions in the cash market for each type of security in each quarter, λ_{jt}. These indices have the advantages that they are available and measured consistently for six of the seven SCOOS asset classes and that they are matched exactly to the SCOOS terms across both asset classes and time. However, because they are unfamiliar and somewhat difficult to interpret quantitatively, it is important for us to compare them to other available measures of market conditions.

Table 5 reports correlations of the SCOOS index for changes in liquidity with other variables in our dataset. As above, shading indicates variables for which we have only time-series data, while other columns are matched by asset class. Our liquidity indices display strong correlations with most other measures of market liquidity and volatility. Indeed, their correlations with liquidity and volatility are higher than the correlations we observed for our indices of funding terms in Table 4. The correlations with the Amihud measure of liquidity, for the two asset classes where those data are available, are in excess of 50%. These observations validate our use of these measures as indices of overall liquidity and market functioning.

To investigate these relationships further, Table 6 reports regressions of the SCOOS liquidity indices on other measures of liquidity that are available for the two corporate bond series. These are the only asset classes for which we have asset-specific Amihud liquidity measures. The regressions fit well, and both of the right-hand-side liquidity measures are significant with the expected sign. In contrast, asset-class-specific realized volatility is not significant, indicating that the SCOOS liquidity measure is not simply picking up changes in broad market conditions. Thus, at least within these two asset classes, the indices do indeed appear to be accurately summarizing liquidity conditions in their respective markets.

[22]Through a different mechanism, Garleanu and Pedersen (2011) also predicts a negative relationship between funding terms and risk-free rates.

5 Determinants of terms

It is clear from the preceding simple correlations that the terms on securities financing change together with market conditions. In particular, dealers report tightening terms more often during periods of market stress. However, measures of market stress are highly correlated with each other, making it difficult to discern which are most connected to securities-financing conditions.

To understand better which variables matter most, we run multivariate regressions of our diffusion indices of changes in terms on subsets of the other variables. Because of the relatively small sample, we restrict ourselves to parsimonious specifications. The variables we include in our baseline models are those that appeared unconditionally important in Table 4, those for which we have data across most of the SCOOS sample, and those that seem likely important on *a priori* grounds. Specifically, for each of the four indices of changes in terms i (spreads, haircuts, etc.), and for each asset class j, we estimate

$$\tau_{i,j,t} = \alpha_{i,j} + \boldsymbol{\beta}_{i,j}\mathbf{x}_{j,t} + \boldsymbol{\gamma}_{i,j}\mathbf{y}_t + e_{i,j,t} \tag{2}$$

where $e_{i,j,t}$ is a normally distributed iid error term; $\mathbf{x}_{j,t}$ is a vector containing the SCOOS indices of funding demand and liquidity and the realized volatility of the security-return index, all of which are measured at the asset-class level; and $\mathbf{y}_t$ is a vector containing the following time-series variables: the percentage change in book dealer equity, the high-yield CDX, the VIX, 10-year swaption-implied interest-rate volatility, and the 3-month Treasury bill rate. (Because the required data do not exist, we cannot include the liquidity indices in the regressions for equities nor realized volatility in the regressions for private RMBS.) In addition to this baseline model, we also ran a number of other specifications and obtained similar results. Some of these alternative models are reported in the Internet Appendix, and we mention a few highlights from them in the text below.

We also run aggregated models, pooling the data across asset classes and including asset-class-level fixed effects. These specifications add power, under the assumption that coefficients are similar across asset classes. The first pooled specification is simply the panel version of our cross-sectional model, which includes the time-series data as regressors:

$$\tau_{i,j,t} = \alpha_{i,j} + \boldsymbol{\beta}_{i}\mathbf{x}_{j,t} + \boldsymbol{\gamma}_{i}\mathbf{y}_t + e_{i,j,t} \tag{3}$$

We also consider specifications that include quarterly time dummies and drop the time-series data:

$$\tau_{i,j,t} = \alpha_{i,j} + \boldsymbol{\beta}_i \mathbf{x}_{j,t} + \delta_{i,t} + e_{i,j,t} \tag{4}$$

The latter specification maximizes the explanatory power for the pooled data, at the cost, of course, of obscuring the sources of common time-series variation. In all of the pooled models, we consider a sample that excludes both private MBS, for which we do not have realized volatilities, and equities, for which the SCOOS does not collect the liquidity measure, as well as a sample that excludes only the equities.

Table 7 presents the results of the baseline models using the full sample.[23] The interpretation of the coefficients in this table is the net percentage of dealers that tighten each term type when there is a one-unit change in the independent variable. To get a better sense of the economic significance of these results, Table 8 reports standardized versions of the coefficients—that is, the number of standard deviations of each dependent variable associated with a one-standard-deviation change in each independent variable—using the pooled specification with five asset classes and time-series control variables. (For parsimony, we report standardized coefficients for only this specification, which is the only pooled model that allows us to estimate the coefficients on all of the variables. However, the results for the other pooled models and the disaggregated models, where comparable, are similar.)

Given the very large movements in the data in the second quarter of 2020 amid the outbreak of the COVID-19 crisis, one concern is that the observations from that quarter could be driving the results in Tables 7 and 8. This turns out not to be the case. Table 9 summarizes the results, in a way that is comparable to Table 8, when we drop Q2 2020. (Full results are reported in Internet Appendix Table A.2.) We lose a small amount of statistical power dropping these observations, but the signs, magnitudes, and significance patterns are broadly preserved.

Below, we highlight and elaborate three main results from these regressions: (1) liquidity is the variable that has the strongest conditional association with funding terms; (2) to a lesser extent, funding demand and dealer balance-sheet condition also matter; and (3)

[23]We use heteroskedasticity-robust standard errors for the cross-sectional models (2) and the pooled models that include time dummies (4). For the pooled models with the time-series controls (3), we cluster standard errors by date. (We cannot cluster for the pooled models with time dummies because of insufficient degrees of freedom.) As noted above, since the data are all effectively in differences, serial correlation is not a serious concern.

conditional on these factors, other risk measures are insignificant.

5.1 Liquidity

Regardless of specification, liquidity appears as the most statistically and economically significant variable for all four terms indices. It is statistically significant at the 1% level in all of the pooled regressions and for most of the disaggregated asset-class regressions where this measure is available. When significant, the coefficient values in individual asset classes range from -0.32 to -0.56 for spreads and haircuts and from -0.19 to -0.46 for maximum amounts and maximum maturities. The pooled regressions using explicit controls also give coefficient values in these ranges. (The pooled regressions using time dummies have somewhat smaller coefficients on liquidity, for reasons we discuss below.) This indicates, for example, that when a dealer believes that liquidity has worsened in a given market he has about a 1/3 to 1/2 chance of tightening his financing spreads and haircuts in response. Looked at another way, as shown in Table 8, a one-standard-deviation change in the liquidity index is associated with a change in the indices of funding terms of about two-thirds of a standard deviation, depending on the market. None of these results is driven by the large movements during the COVID-19 crisis; indeed, comparison of Tables 8 and 9 shows that, if anything, the economic significance of liquidity is a bit stronger in the sample that excludes the COVID-related observations. Robustness checks reported in the Internet Appendix show that this result is also insensitive to alternative vectors of control variables.

The statistical and economic significance of liquidity is weaker in the pooled model with time dummies (last two columns of Tables 7a through 7d) than in the pooled model with the time-series controls. For example, for financing rates the coefficients are only about -0.3, rather than -0.5. However, there is reason to think that the model with the time dummies understates the importance of liquidity. Namely, the coefficients in that model reflect only the liquidity effect *within* asset classes, even though it is known that there is a common component to liquidity across markets (e.g., Chordia, Sarkar, and Subrahmanyam, 2005; Fontaine and Garcia, 2012). The effects of any such component will not be reflected in the liquidity coefficient estimates in these models and would instead be swept into the coefficients on the time dummies themselves. To provide some rough evidence that the time fixed effects are themselves largely reflective of liquidity conditions, we extract their coefficients and examine their time-series correlations with other time-series variables.

Table 10 shows the results. The time fixed effects are indeed highly correlated with the cross-asset-class average of the SCOOS liquidity series, with the correlations for the financing spreads and haircut regressions on the order of 70%. Of course, the fixed effects are correlated with other series as well (just as liquidity is). In particular, they have strong associations with the CDX index and the T-bill rate, though much of the latter turns out to be driven by the COVID-19 observations. In any case, these correlations are suggestive that a significant portion of the comovement across different funding terms and asset classes may be driven by the common component of liquidity.

5.2 Funding demand and dealer condition

Returning to Tables 7 and 8, we note two further significance patterns. First, stronger demand for securities financing is significantly associated with tighter indices of financing spreads. In all of the models of financing spreads that pool the data across asset classes, the coefficient on the funding demand index is statistically significant at the 1% level and has a magnitude of about -0.2, indicating that when dealers see demand for funding increasing they raise their spreads about 20% of the time. One interpretation is that the supply of lending is somewhat inelastic. The coefficients on demand for the other three terms indices, in contrast, are small and insignificant.[24]

Second, deteriorations in dealer equity levels are associated with higher financing spreads and haircuts among riskier and less-liquid collateral types. The percentage change in dealer equity is statistically significant in our regressions of spreads and haircuts for ABS, CMBS, and private-label RMBS. In the asset-class-specific models, the significant coefficient values range from -0.93 to -5.97, indicating that a sector-wide decline in dealer equity of 10 percent would be associated with 10 to 60 percent of dealers tightening their spreads and haircuts for these asset classes. In the pooled models, the coefficients range from -1.3 to -2.3, though they are not always statistically significant. As shown in Table 8, these values are consistent with a one-standard-deviation quarterly change in dealer equity resulting in about a 0.15-

[24]In the sample excluding the COVID-19 crisis, shown in the Internet Appendix, the demand coefficient is statistically significant with a *negative* sign in the regressions for maximum amounts and maximum maturities. This could be consistent with dealers expanding the amount of leverage they are willing to provide in response to higher demand, even as they also increase the rate charged to provide that leverage.

standard-deviation change in our indices of spreads and haircuts, a marginal level of economic significance.

This result suggests that dealers tighten terms, particularly on riskier collateral, to protect capital in times when their balance sheets become more fragile. That basic conclusion holds regardless of how dealer condition is measured. Internet Appendix Table A.3 shows that when we replace dealers' equity growth with their asset growth, changes in their leverage ratios, or changes in their excess CDS spreads, we continue to find significant responses of spreads or haircuts (or both) among the less-liquid asset classes. Meanwhile, there is only weak evidence of responses among more-liquid asset classes. (The significance of liquidity, emphasized above, is unchanged in these alternative specifications.)

5.3 Other risk measures

Although the Treasury bill rate appears consistently with a significant negative sign, measures of asset-market volatility and credit risk are not generally important in these regressions. The CDX index and volatility measures have coefficients that are almost always small and insignificant, which is particularly notable in light of their fairly strong *unconditional* correlations with funding terms. Evidently, given liquidity conditions, funding terms are relatively insensitive to market volatility and credit risk.[25] The lack of significance is robust to alternative specifications that measure risk and volatility using different variables and omit the Treasury bill rate from the model. (See Internet Appendix table A.4.)

6 Understanding the results: a simple model

Summing up the above empirical findings, we have shown that (1) dealers change financing spreads, haircuts, and other financing terms in a highly positively correlated way; (2) the primary driver of all of these funding terms is the liquidity of the underlying securities markets; (3) dealer balance-sheet constraints also play a significant role in funding conditions, particularly for less-liquid security types. As noted earlier, the theoretical literature is somewhat inconclusive on these issues, and it is not clear that any extant theoretical model

[25]This absence of such a relationship in our data is broadly consistent with the findings of Baklanova et al. (2019).

could rationalize our results. In this section, we therefore sketch a simple theoretical framework that is consistent with the main patterns we have documented. Because our primary interest in this paper is empirical, the model abstracts from a number of technical issues and is partial-equilibrium in the sense that it does not fully specify the structural sources of the shocks facing the dealer. Nonetheless, it should help to clarify some plausible market dynamics that could underly our findings.

The model adapts Barsky, Bogusz, and Easton (2022), which in turn is a special case of Simsek (2013). Consider a security with unknown payoff s. The number of shares of the security outstanding is normalized to unity. There are two agents in the model: dealers and clients. For simplicity, we assume that dealers and clients are both risk-neutral, have no time preference, and perceive identical subjective probability distributions over the payoff of the security. Specifically, let the probability density of s be uniform over the range $[1-\sigma, 1+\sigma]$. Thus, σ measures the riskiness of the security. In period 1, s is revealed, and the holder of the security receives this payoff in period 2.

Clients are endowed with capital c and, in addition, borrow an amount $l \geq 0$ from dealers in order to fund purchases of the security in period 0. The security serves as collateral for the loan, with haircut h and financing rate r, both of which we will solve for. We normalize the dealer's own funding cost to zero, so that r is also the financing spread. Clients must hold all securities in equilibrium, so $l + c = p$, where p is the (endogenously determined) time-0 security price. If s turns out to be less than the promised repayment value of the loan, $l(1 + r)$, the client defaults on the loan in period 1 and the dealer takes possession of the security.

We introduce two additional sources of uncertainty into the dealer's problem. First, we assume that, with probability λ, the security market experiences a "liquidity freeze" in period 1. In this case, although the security's fundamental value is known to be s, it is temporarily only possible to sell it for a price below this value, which we take to be $1 - \sigma$. Second, we assume that, with probability b, the dealer receives a "balance sheet" shock, whereby he experiences a sudden, unexpected need for cash. If the balance-sheet shock occurs, the dealer can raise the cash either (1) by using the funds returned by the client, if the client has not defaulted, or (2), if the client has defaulted, by selling the security received as collateral. In the latter case, the dealer recovers the full value of the security if there is not simultaneously a liquidity freeze, but if there is a liquidity freeze the dealer only receives the fire-sale value $1-\sigma$.[26] Thus, in addition to the risk associated with the repo position itself, the dealer also faces a risk of forced sale in illiquid conditions. This happens if the liquidity and balance-sheet shocks are both realized, which occurs with probability λb, and the client defaults, which occurs with probability $\Pr[s < l(1+r)]$. (Implicitly, we assume that clients are patient investors who are not subject to balance-sheet shocks.) For simplicity, we assume these three events are independent, although in reality all three are clearly likely to occur together during times of severe market stress. The possible outcomes of the model are summarized in Figure 2.

The model can be solved in closed form for the security price, loan amount, repo haircut, and financing spread as of time 0. The solution is derived in the Appendix. Our interest is in how equilibrium spreads and haircuts respond to different changes in the environment. Let $V \equiv \max\left[\sqrt{\sigma}-\sqrt{c}, 0\right]$, reflecting the portion of asset risk not absorbed by client capital. Then, we can show

$$r = \frac{(1+\lambda b)V^2}{1-c-\lambda b V^2} \tag{5}$$

$$h = \frac{c}{1-\lambda b V^2} \tag{6}$$

A number of special cases are worth noting. First, if $c \geq \sigma$ (so $V = 0$), dealers are fully protected from default. Consequently, financing spreads are always zero, and haircuts are unresponsive to marginal changes in any of the three types of risk. This case is similar in spirit (though different in details) to the binomial model of Geanakoplos (2003) and Fostel and Geanakoplos (2015), in which a "no default" equilibrium always exists where haircuts are set to ensure that dealers are fully protected from downside risk. At the other extreme, if $\lambda = 0$ or $b = 0$, financing spreads fully adjust to compensate the dealer for the risk of loss on the repo position. Haircuts are unresponsive to changes in σ in this case as well.[27]

In the case where default is possible ($c < \sigma$) and liquidity and balance-sheet shocks are present ($\lambda > 0$ and $b > 0$), it is straightforward to show that haircuts and spreads both move in the same direction in response to changes in λ, b, and σ but in opposite directions in response to changes in c. Our main empirical result that spreads and haircuts move

[26] The idea of the liquidity freeze is similar to Acharya, Gale, and Yorulmazer (2011). Oehmke (2014) endogenizes this type of price dynamic and ties it to repo lenders' balance-sheet constraints.

[27] If dealers and clients differed in their beliefs about s, haircuts would generally respond to asset-price uncertainty, even in cases where $\lambda = 0$ or $\beta = 0$, similar to the example considered by Barsky, Bogusz, and Easton (2022).

together and both respond primarily to changes in liquidity is thus consistent with a version of the model in which fluctuating concerns about illiquid conditions, reflected in λ, drive the market. Intuitively, when client capital is not sufficient to cover downside risk in the security value, the dealer is always exposed to the possibility of default. When it becomes more likely that the dealer will also need to dispose of the collateral in illiquid market conditions, the expected cost of the default state increases and he requires a higher spread on the repo to compensate. This higher funding cost reduces the client's expected net payoff on the position, putting downward pressure on the security price, which, for a given value of c, implies a higher haircut in equilibrium.

In the aggregate data on spreads and haircuts, the responses to dealer balance-sheet constraints are weaker (or, at least, less precisely identified) than the responses to liquidity. But it is interesting to note that the effects of dealer equity are most pronounced among the less-liquid securities in our sample. This is consistent with the model, which has b and λ *interacting* to determine both haircuts and spreads. If we suppose that securities like ABS, CMBS, and private RMBS generally have a greater chance of experiencing illiquid trading conditions, then the theory predicts that both haircuts and financing spreads on these types of securities should be more sensitive to dealer balance-sheet risk than the terms on other types of securities, which is what we find.

The model's predictions with respect to client capital c are less directly related to our empirical tests but nonetheless have some suggestive implications. More client capital can be thought of as corresponding to lower funding demand, since the quantity of securities that needs to be funded remains unchanged when c increases. In this sense, the model is consistent with our empirical result that lower demand causes funding spreads to fall. The model also predicts that lower demand (higher client capital) results in higher haircuts, a hypothesis that we cannot confirm in the data. However, it is the case that the response of haircuts to demand in the SCOOS is insignificant even though the response of spreads is significantly positive, which is suggestive of a mechanism at least partially working in this direction.

Like the more-sophisticated models already present in literature, the theory we have sketched here contains no role for maturity or position limits, which we also find to be important margins of adjustment in the data and to respond similarly to liquidity. A fruitful direction for future research could be to consider incorporating these elements into a theoretical framework like this one.

7 Do Funding Conditions Affect Market Conditions?

In models like Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009), the availability of securities financing affects liquidity and pricing in cash securities markets. In this section, we test for this idea by instrumenting funding terms. Our instruments are based on the reasons that senior credit officers themselves report for changing terms. These responses are of some interest in their own right. We first describe these additional data and then turn to the instrumental-variables analysis.

7.1 Self-reported reasons for changing terms

In addition to the questions described above, the SCOOS asks dealers who report changing either price or nonprice terms in a given quarter the reasons that they did so. Specifically, it contains a series of questions like the following, by counterparty type:

> *To the extent that the price or nonprice terms applied to hedge funds have tightened or eased over the past three months ... what are the most important reasons for the change?*
>
> *Possible reasons for tightening:*
>
> __ *Deterioration in current or expected financial strength of counterparties*
> __ *Reduced willingness of your institution to take on risk*
> __ *Adoption of more-stringent market conventions*
> __ *Higher internal treasury charges for funding*
> __ *Diminished availability of balance sheet or capital at your institution*
> __ *Worsening in general market liquidity and functioning*
> __ *Less-aggressive competition from other institutions*
>
> *Possible reasons for easing:*
>
> __ *Improvement in current or expected financial strength of counterparties*
> __ *Increased willingness of your institution to take on risk*
> __ *Adoption of less-stringent market conventions*

__ *Lower internal treasury charges for funding*

__ *Increased availability of balance sheet or capital at your institution*

__ *Improvement in general market liquidity and functioning*

__ *More-aggressive competition from other institutions*

Dealers are asked to select the first, second, and third most-important reasons from the above lists of seven. There is also an "other" option available, but it is rarely used and we disregard it. Only dealers who report a change in their terms answer these questions, and they provide this information for each of seven different counterparty types: hedge funds, nonfinancial companies, and insurance companies since the survey began, and several others since it was revised in 2011.[28]

We note that the "terms" being asked about in these questions cover those on both securities financing and OTC derivative activity. This means that the answers must be taken with a grain of salt when drawing conclusions about securities financing alone. However, it does not affect their potential use as instruments, since, as long as dealers' responses at least *partially* reflect the securities-financing market, they should be correlated with funding terms. We will exploit this correlation in the next subsection.

To measure the importance of the various motivations for changing terms across time, we construct the variables

$$x_{k,l,t} = \frac{\#_{\text{t}} \text{ tighten to cntrprty } k \text{ for reason } l - \#_{\text{t}} \text{ ease to cntrprty } k \text{ for reason } l}{\text{total respondents}_t} \tag{7}$$

for each of the seven reasons and each of the six counterparty types. Table 11 shows how often each reason is listed as an important reason for changing terms. The frequencies of reasons for changing terms are fairly consistent across counterparty types. For all counterparties, "competition from other institutions" is the most-frequently cited reason for changing terms. Yet, while this rationale may make perfect sense from the perspective of an individual dealer, it is not a satisfying explanation for aggregate fluctuations in terms since that there are

[28]Prior to 2011 Q3, rather than selecting the top three reasons, dealers were asked to rate each possible reason for changing terms as "very important," "somewhat important," or "not important." However, it turns out that the number of reasons that dealers listed as "very important" always averaged about three. Thus, for our purposes, we take "top-three reason" and "very important reason" to be synonymous, and we splice the series together.

not large changes in the market structure of the broker-dealer industry from quarter to quarter. Changes in "competition" likely reflect dealers observing each other tightening and easing terms, the ultimate cause of which is one of the other reasons listed. Apart from competition, dealers generally cite market liquidity as the most common reason for changing terms. Indeed, when we regress our individual funding-term indices $\tau_{i,j,t}$ on the seven indices of reasons for changing terms $x_{k,l,t}$, the "competition" is never statistically significant. (See Internet Appendix Table A5.) This supports the idea that competition is not an important reason for changing terms, conditional on other possible reasons, even though it appears important in an unconditional sense. Meanwhile, the $x_{k,l,t}$ series for "liquidity and market functioning" is significant and large in these regressions for all four terms, consistent with the strong correlation shown above between terms and liquidity, as measured both by the SCOOS and by external market measures.

7.2 Instrumental Variables Analysis - Liquidity

We estimate the effects of funding terms on market liquidity by two-stage least squares, where as instruments we use the percentages of dealers reporting changing terms because of the adoption of new "market conventions." Because these responses generally reflect changes in regulatory requirements and industry standards whose timing is not tied to specific market developments at a quarterly frequency, the instruments should satisfy the exclusion criterion for exogeneity. As noted, there are three different counterparty types that are asked about over over the entirety of our sample. The three corresponding series for the frequency of citing "market conventions" are depicted in Figure 3. As can be seen, they are only modestly correlated with each other, consistent with the claim that they are driven by idiosyncratic institutional factors, rather than by broad market developments.

In the first stage, our indices of funding terms are regressed on the net percentage of dealers changing terms because of market conventions. To conserve degrees of freedom, we run these regressions as panels across asset classes, and we include the same vector of control variables that we used in Table 5:[29]

$$\tau_{i,j,t} = \alpha_{i,j} + \sum_k \beta_{i,j,k} x_{k,t} + \gamma_i \mathbf{y}_{j.t} + e_{i,j,t} \tag{8}$$

where k indexes counterparty type and $i = \{\text{financing spread, maximum amount}\}$. Univariate tests indicated that the net fractions of dealers reporting tightening terms because of market conventions to hedge funds and nonfinancial corporations were strong instruments for financing spreads and maximum amounts, but they were weaker instruments for haircuts and maximum maturities. In addition, the net fraction of dealers reporting tightening terms because of market conventions to insurance companies appeared to be weak as an instrument for all types of funding terms.[30] We therefore use the responses having to do with market conventions for hedge funds and nonfinancial companies as our instruments and, since we cannot have more endogenous variables than instruments, we focus on the possible effects of financing spreads and maximum amounts on liquidity. Results using other combinations of terms and instruments, though more likely to suffer from weak-instrument problems, are broadly similar.

Because our variable of interest is market liquidity, we exclude the equities asset class, which does not have a reported liquidity series, from this analysis. We run the regressions both with and without the private RMBS asset class, since its inclusion prevents us from controlling for realized volatility. Full results of the first stage are reported in Internet Appendix Table A.6.

The second-stage regression is

$$\lambda_{j,t} = \eta_j + \delta_{\text{fin.spr.}} \tilde{\tau}_{\text{fin.spr.},j,t} + \delta_{\text{max.amt.}} \tilde{\tau}_{\text{max.amt.},j,t} + \zeta \mathbf{y}_{j,t} + u_{j,t} \tag{9}$$

where $\tilde{\tau}_{i,j,t}$ are the fitted values from (8) and η_j is an asset-class fixed effect. Table 12 presents

[29]Note that the vector of control variables here, $\mathbf{y}_{j.t}$, contains variables that vary across asset classes (funding demand and realized volatility) as well as variables that only vary over time (the other controls used above.

[30]Specifically, as a preliminary variable-selection approach, we ran our first stage regression for each funding term series on each possible instrument (and controls), one at a time. Of the twelve regressions, the two largest F statistics were 17.4, for financing spreads on the nonfinancial-corporation series, and 68.4, for maximum amounts on the hedge fund series. Both of these exceed the 5% Mitaki-Pflueger (2015) robust critical values to reject weak instrumentation. The series for insurance companies was never significant by this standard.

the results. In both cases, the two instrumented funding terms have the anticipated sign but are insignificant at the 10% level. On the other hand, a Wald test rejects that they are jointly zero.

To see more clearly the importance of funding terms for liquidity in different states of the world, we construct estimates of the total effect of terms on liquidity in each period for each asset class. That is, we compute the estimated quantities $\delta_{\text{fin.spr.}}\tilde{\tau}_{\text{fin.spr.},j,t}+\delta_{\text{max.amt.}}\tilde{\tau}_{\text{max.amt.},j,t}$. Since the δ coefficients are estimates of the causal effect of terms on liquidity, these series represent unbiased estimates of the joint effect of the indices of funding terms on the indices of market liquidity at each observation. Figure 4 plots these estimated effects. It is clear from the figure that, in most periods for most asset classes, there is no meaningful economic impact of the terms indices on the liquidity indices, whether or not the difference is statistically significant. In other words, funding conditions have little effect on market liquidity most of the time. The only clear exception is the last observation, associated with the market turmoil of 2020. In this period, we estimate the effect of terms to be negative, significant, and large for all asset classes.[31] Evidently, funding conditions contributed to the deterioration in liquidity in these markets during this period. Indeed, though there is some variation across asset classes, overall we estimate that the tightening of funding terms was responsible for approximately half of the decline in our liquidity metric during the second quarter of 2020.

7.3 Instrumental Variables Analysis - Returns

We next ask whether there is any relationship between financing conditions and asset prices. Table 4 illustrated moderate unconditional correlations between terms and security returns. Table 13 examines these relationships controlling for other factors and using the same instrumenting procedure as above. Because asset returns are likely to be strongly affected by the economic outlook, we also include in these regressions quarterly revisions to one-year-ahead consensus forecasts of real GDP from the Blue Chip Economic Indicators. On the other hand, we omit the high-yield CDX index from our vector of controls, since it effectively embeds the same information as high-yield bond returns and is likely to be highly correlated with returns on other asset classes as well. We omit private-label MBS from this analysis because we do not have a return series for that asset class.

[31] The observed deterioration in corporate-bond liquidity is consistent with other studies that have examined this period, such as Kargar, Lester, Lindsay, Liu, Weill, and Zuniga (2021).

Once again, the net fractions of dealers reporting tightening terms to hedge funds and nonfinancial corporations because of market conventions appeared to be strong instruments for our indices of changes in financing spreads and maximum funding amounts, while the other funding terms indices appeared to be more weakly instrumented. (See Internet Appendix Table A.6.) Yet, also as in the liquidity regressions, terms are individually statistically insignificant in the second stage. Moreover, in this case, Wald tests do not strongly indicate joint significance of the two funding terms, particularly in the sample that includes the equities. One contributing factor may be that asset classes differ substantially in the volatility of their returns, so pooling may be inappropriate. As with the effects of funding terms on liquidity, these are also generally economically small effects. However, during the stress of March 2020, they imply asset-price declines of roughly 2% to 6% due to the extreme term tightening. For comparison, the total net changes in our asset-price indices ranged from +3% (agency MBS) to -9% (high-yield corporate bonds) during this quarter. Thus, again, there is some evidence that funding conditions can have substantial effects on cash asset markets during periods of very high market stress, although these effects are weakly identified in our data.

Finally, we can also consider how portfolios of different assets are affected by changing funding conditions. We do this by estimating versions of the 2SLS procedure described above separately for each asset class (other than private MBS) and combining the estimated coefficients on funding terms with the relevant variances and covariances of those terms. Specifically, for each of the six asset classes, we search across funding term-instrument combinations to find the "market conventions" series that produce the highest F statistics in the first stage. For agency MBS, high-yield corporate bonds, and ABS, the F statistics exceeded 10 for at least one term-instrument pair. For CMBS and equities, the F statistics were always below 10, indicating that weak instruments could be a problem. Thus, we perform the analysis both with and without those asset classes. With the 2SLS estimates in hand, we calculate the return volatility stemming from funding terms for a given asset class by multiplying the variance of each funding-term index by the square of the regression coefficient.[32] The results are reported in the top six rows of Table 14. According to these estimates, chanes in funding terms, as we measure them, contribute nearly 2% to the un-

[32]The second stage coefficients are negative and statistically significant at the 10% level for agency MBS, ABS, and both classes of corporate bonds.

conditional standard deviation of high-yield corporate bond returns, holding other factors constant (a number that includes the potentially influential observations in early 2022). In contrast, they appear to contribute almost nothing to the volatility of equity returns. The latter result is intuitive both because terms for equities change less often than those for other asset classes (see Table 3) and because equity trading relies less heavily on the repo market than fixed-income trading does, though we caution again that the equity results are imprecisely estimated.

To consider portfolios of multiple assets we combine the coefficients on the funding-terms indices in the individual asset-class level regressions with the corresponding elements of the variance-covariance matrix of different funding-terms indices across asset classes and an assumed vector of portfolio weights. The middle rows of Table 14 show the results for equally weighted portfolios. Equal weighting dramatically reduces portfolio volatility resulting from funding terms relative to individual fixed-income assets, through diversification. This is even true when the relatively insensitive equities asset class is excluded. When we solve for the portfolio weights that minimize the volatility of returns stemming from funding terms, as shown in the bottom rows of the table, we find not surprisingly that most weight ends up on equities and term-related volatility is reduced to just 0.09%. When we exclude equities (and CMBS) from consideration, the minimum-variance portfolio puts almost all of the weight on investment-grade corporate bonds and ABS. Even here the term-related volatility is just 0.33%, well below any of the individual fixed-income assets. We conclude that, to the extent that bonds are exposed to return volatility stemming from financing conditions, this exposure can be significantly reduced by diversifying across asset classes.

8 Conclusion

This paper has presented new evidence on the workings of the bilateral, dealer-to-client securities-financing market, an important source of leverage for hedge funds and other securities-market participants and an epicenter of recent financial crises. By exploiting information from the Senior Credit Officer Opinion Survey, we demonstrate several facts about this market that have not previously been systematically documented. Although the SCOOS data have certain limitations, they are the only source of data to cover dealer-to-client financing across a variety of asset classes and encompassing the bulk of the activity in the market. We thus add new evidence on this important segment of the short-term funding complex, complementing studies on other pieces of the repo market such as Gorton and Metrick (2012a), Krishnamurthy, Nagel, and Orlav (2014), and Copeland, Martin, and Walker (2014).

Our main findings are that, during the 2010 - 2020 period, different funding terms generally moved together with each other, and that these movements were highly correlated with broad conditions in the underlying securities markets. In particular, cash-market liquidity appears to have been the most important determinant of how terms were set. Our results present some challenges for theoretical work in this area. In papers such as Gromb and Vayanos (2002), Geanakoplos (2003), Garleanu and Pedersen (2011), and Araujo, Kubler, and Schommer (2012) have different implications, or ambiguous implications, for the co-movement of financing spreads and haircuts, and these terms depend largely on volatility and credit risk. Meanwhile, very few theoretical models explicitly incorporate position or maturity limits. In contrast, our results suggest that adjustments to financing terms are driven primarily by liquidity, that fluctuations in liquidity drive *all* types of financing terms, and that these moves are almost always in the same direction. We also find that dealer financial condition is a significant, though less important, determinant of funding terms, especially for less-liquid asset classes. The simple theoretical framework we sketched points toward one way of rationalizing these findings.

We find little evidence that changes in financing terms have been important for liquidity or asset returns during most of the post-GFC period, though they do seem to have played a significant role for riskier asset classes during the COVID-19 crisis. Broadly speaking, these findings support models of the repo market, such as Brunnermeier and Pedersen (2009), in which funding conditions are typically not binding but can have important effects during periods of extreme market stress.

A Derivation of funding terms in equilibrium model

Let $\bar{s}$ be the endogenous security value below which the client defaults. In equilibrium, we must have

$$\bar{s} = l(1+r) \tag{10}$$

In terms of this value, since we are assuming that s is uniformly distributed over $[1-\sigma, 1+\sigma]$, the probability of default is

$$\Pr_{\text{def}} = \frac{\bar{s}-(1-\sigma)}{2\sigma} \tag{11}$$

Because the dealer is risk-neutral the value of the loan must be equal to his expected payoff. This is given by

$$l = \lambda b \Pr_{\text{def}}(1-\sigma) + (1-\lambda b)\frac{1}{2\sigma}\int_{1-\sigma}^{\bar{s}} s ds + (1-\Pr_{\text{def}})\bar{s} \tag{12}$$

$$= \frac{2\bar{s}(1+\sigma) - \lambda b(\bar{s}+\sigma-1)^2 - (\sigma-1)^2 - \bar{s}^2}{4\sigma} \tag{13}$$

The time-0 price of the security is determined as follows. If $s \geq \bar{s}$ in period 1, then the client retains the security and receives payoff s. If $s < \bar{s}$, the dealer takes possession of the security, and his payoff is determined by whether there are also liquidity and balance-sheet shocks. By Theorem 2 of Simsek (2013) (and since beliefs are symmetric), the price is equal to the probability of each state obtaining, times the expected payoff of the security holder in each state:

$$p = \lambda b \Pr_{\text{def}}(1-\sigma) + (1-\lambda b)\frac{1}{2\sigma}\int_{1-\sigma}^{\bar{s}} s ds + \frac{1}{2\sigma}\int_{\bar{s}}^{1+\sigma} s ds \tag{14}$$

$$= 1 - \lambda b \frac{(\bar{s}+\sigma-1)^2}{4\sigma} \tag{15}$$

Using the market-clearing condition $p = c + l$ and the constraint that $\bar{s} \geq 1-\sigma$ together with (20) and (15) to solve jointly for $\bar{s}$ and p gives

$$\bar{s} = \max[1+\sigma-2\sqrt{c\sigma}, 1-\sigma] \tag{16}$$

$$= 1 + 2\sqrt{\sigma}V - \sigma \tag{17}$$

and

$$p = 1 - \lambda b V^2 \tag{18}$$

where, as in the text, $V \equiv \max[\sqrt{\sigma} - \sqrt{c}, 0]$. Rewriting l in terms of the solution for $\bar{s}$,

$$\begin{aligned} l &= \frac{2(1 + 2\sqrt{\sigma}V - \sigma)(1 + \sigma) - \lambda b(2\sqrt{\sigma}V)^2 - (\sigma - 1)^2 - (1 + 2\sqrt{\sigma}V - \sigma)^2}{4\sigma} && (19) \\ &= 1 - \sigma + 2\sqrt{\sigma}V - (1 + \lambda b)V^2 && (20) \end{aligned}$$

By definition, the haircut is client capital divided by the security value:

$$\begin{aligned} h &= \frac{c}{p} && (21) \\ &= \frac{c}{1 - \lambda b V^2} && (22) \end{aligned}$$

To find the equilibrium financing rate (spread), rearrange (10) and substitute (17) and (20):

$$\begin{aligned} r &= \frac{\bar{s}}{l} - 1 && (23) \\ &= \frac{1 + 2\sqrt{\sigma}V - \sigma}{1 - \sigma + 2\sqrt{\sigma}V - (1 + \lambda b)V^2} - 1 && (24) \\ &= \frac{(1 + \lambda b)V^2}{1 - c - \lambda b V^2} && (25) \end{aligned}$$

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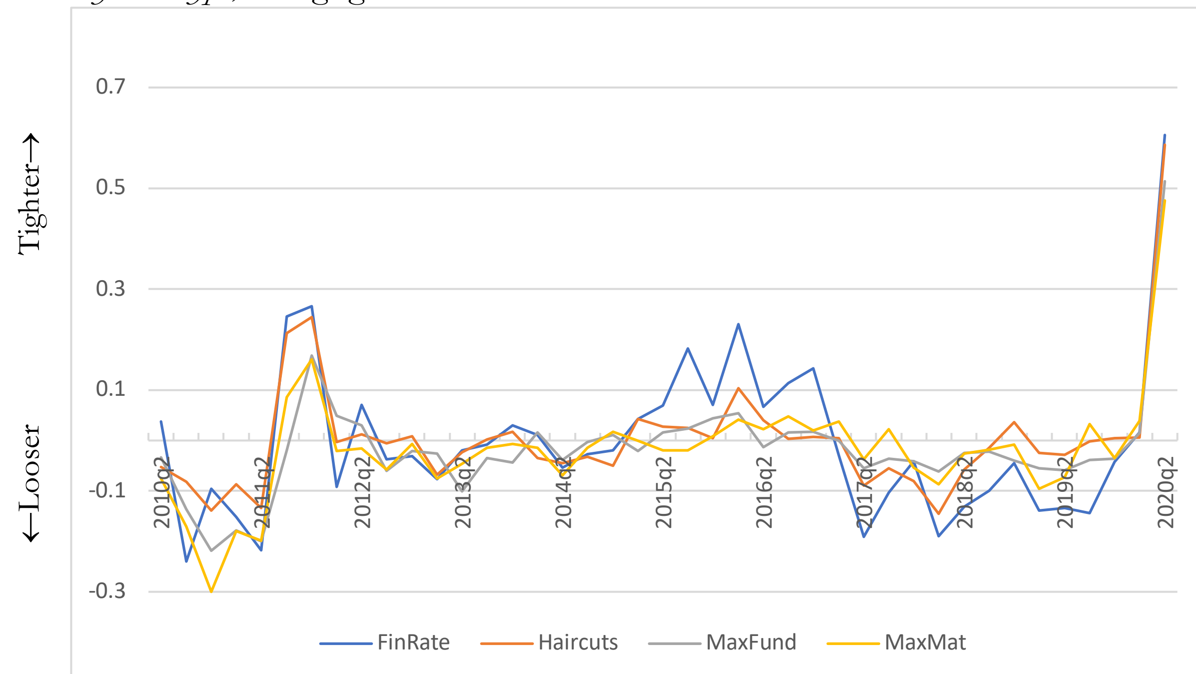
Figure 1. Diffusion indices of changes in funding terms

A. By term type, averaging across all asset classes



B. By asset class, averaging across terms

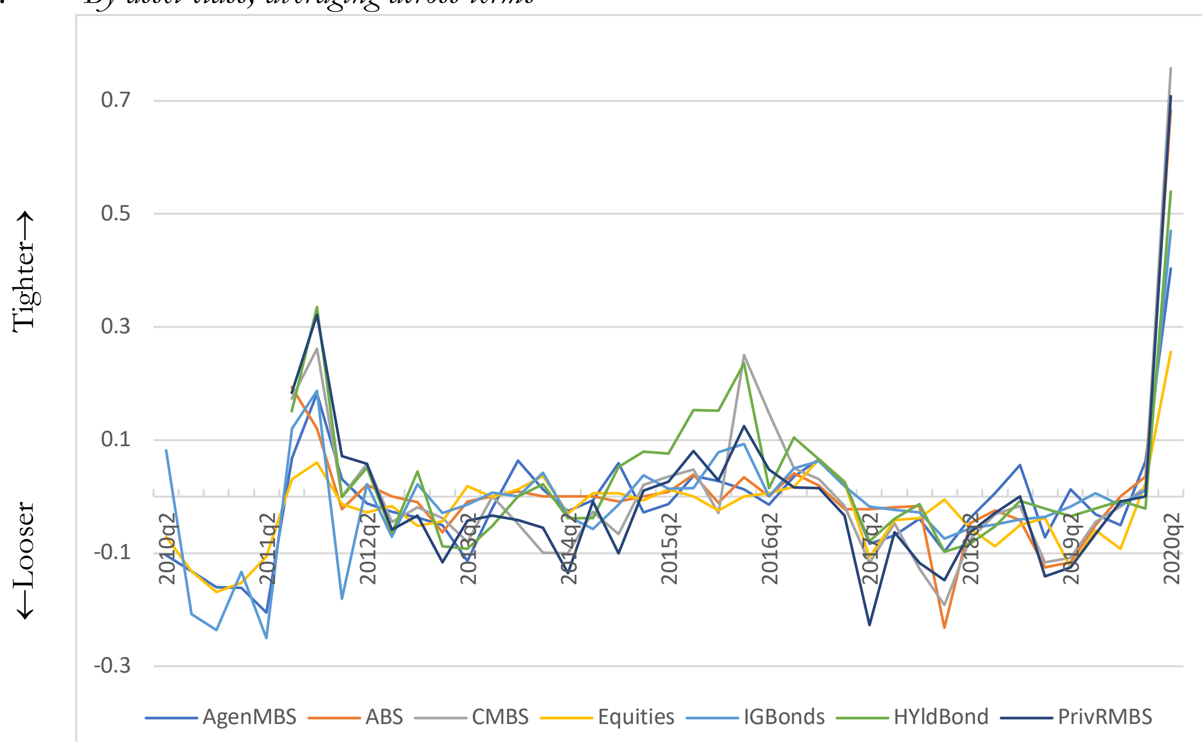


Figure 2. Possible model outcomes

<table>
<tr><th>Security value</th><th colspan="3">$s < l(1+r)$</th><th rowspan="3">$s > l(1+r)$</th></tr>
<tr><th>Balance-sheet shock?</th><th colspan="2">Yes</th><th rowspan="2">No</th></tr>
<tr><th>Liquidity freeze?</th><th>Yes</th><th>No</th></tr>
<tr><td>Outcome</td><td>Default; dealer sells security at fire-sale price</td><td>Default; dealer sells security for fair value</td><td>Default; dealer holds security to maturity</td><td>Loan is repaid</td></tr>
<tr><td>Dealer’s gross payoff</td><td>$1 - \sigma$</td><td>s</td><td>s</td><td>$l(1+r)$</td></tr>
</table>

Figure 3. Net percentages of dealers reporting tightening terms because of the "adoption of market conventions"

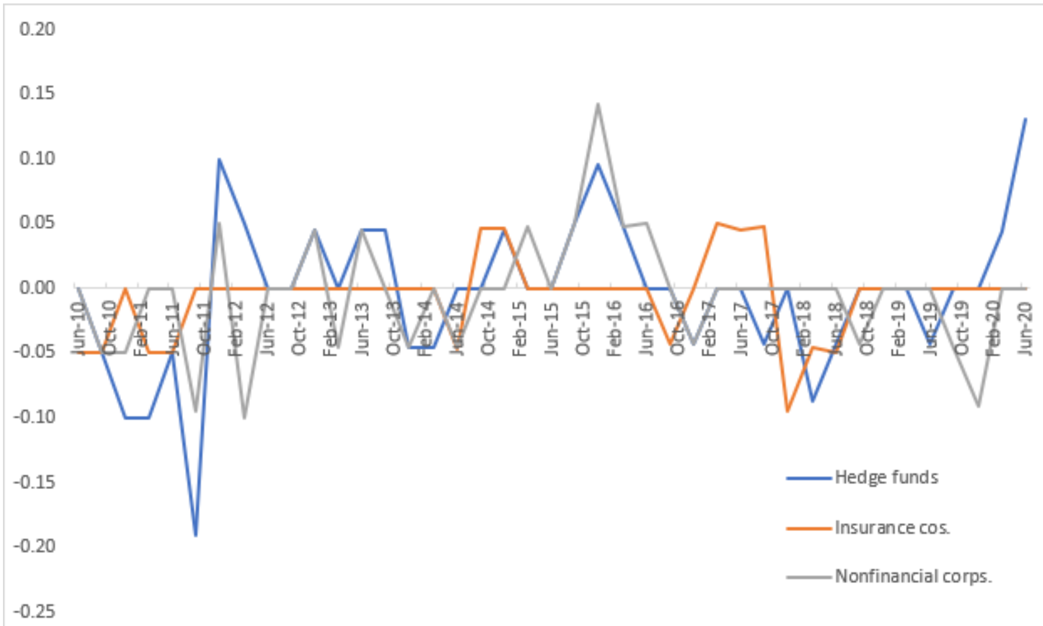
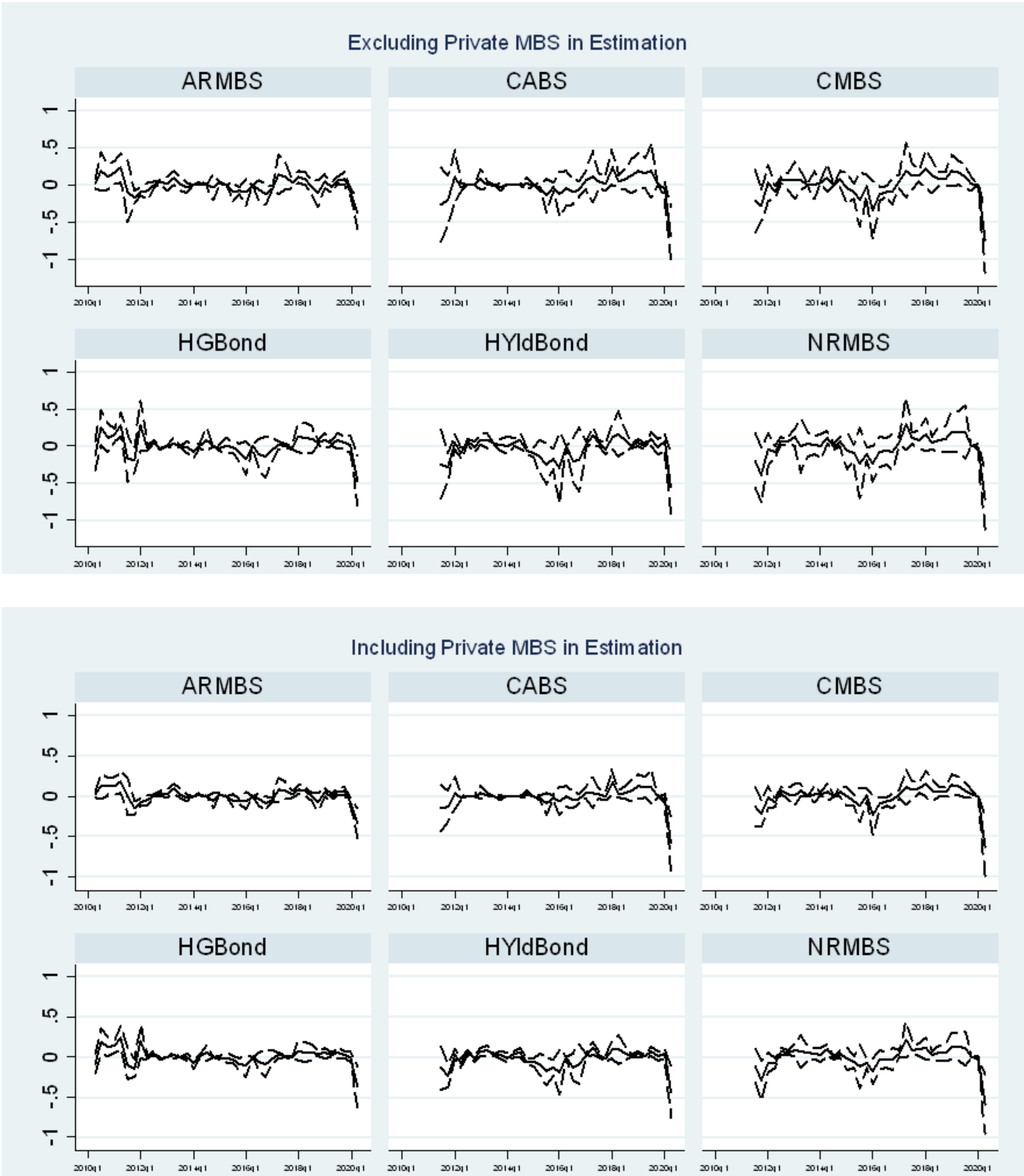


Figure 4. Estimated effects of funding terms on SCOOS liquidity series



Notes: The solid lines show the difference between the SCOOS liquidity series (net fraction of dealers reporting improvements in liquidity and market functioning) and the predicted values of these series based on an exercise using equations (8) and (9), in which we counterfactually impose that securities financing terms did not change. Dashed lines show two-standard-deviation confidence bands.

Table 1. Asset-specific data sources

	Agency MBS	IG Corporate	HY Corporate	Consumer ABS	CMBS	Private MBS	Equities
Returns & realized vol.	Bloomberg Barclays US MBS Index[a]	Bloomberg Barclays US IG Corp. Bond Index[a]	Bloomberg Barclays US Corp. HY Bond Index[a]	Bloomberg Barclays US Agg ABS Index[a]	Bloomberg Barclays US CMBS IG Index[a]	--	S&P 500
Issuance	SIFMA	SIFMA	SIFMA	SIFMA	SIFMA	SIFMA	FOF
Trading volume	SIFMA	SIFMA	SIFMA	SIFMA	SIFMA	SIFMA	NYSE
Financing volume	FR-2004	FR-2004[b]	FR-2004[b]	FR-2004[c] (2015Q1)	FR-2004[c] (2013Q2)	FR-2004[c] (2013Q2)	FR-2004 (2013Q2)
Fails to deliv.	FR-2004	FR-2004[b]	FR-2004[b]	--	--	--	--
Amihud liquidity	--	TRACE	TRACE	--	--	--	--
Tri-party data	FRBNY (2010Q3)	FRBNY (2010Q3)	FRBNY (2010Q3)	FRBNY (2010Q3)	--	FRBNY (2010Q3)	FRBNY (2010Q3)

Notes: The table reports sources of for the asset-class-specific data series that we match to the SCOOS. Dates in parentheses indicate the first date at which the data are available, if the first date is later than 2010Q2. "--" indicates that no data series exists.

[a] Used with permission of Bloomberg.
[b] FR-2004 data is available for corporate bonds as a whole, but is not separated by credit rating.
[c] Beginning in 2013Q2, the FR-2004 reports an "other" category of securities financing that includes structured-finance products. Beginning in 2015Q1, ABS are split out separately.

Table 2. Summary Statistics for diffusion indices of changes in funding terms

			Financing spread	Haircuts	Max. amount	Max. maturity
Sample mean	Unweighted indices	Ave. clients	0.01	0.02	0.01	0.01
		MF clients	-0.00	0.00	-0.02	-0.02
	Weighted indices	Ave. clients	0.00	0.00	-0.00	-0.01
		MF clients	-0.01	-0.02	-0.03	-0.03
Sample std. dev.	Unweighted indices	Ave. clients	0.18	0.14	0.13	0.12
		MF clients	0.17	0.14	0.12	0.12
	Weighted indices	Ave. clients	0.21	0.18	0.15	0.14
		MF clients	0.20	0.17	0.14	0.14
% dealers changing terms		Ave. clients	0.19	0.10	0.14	0.09
		MF clients	0.18	0.11	0.10	0.10
Corr: Ave vs MF clients (unweighted)			0.95	0.95	0.89	0.91
Corr: Ave vs MF clients (weighted)			0.95	0.97	0.91	0.93
Corr: weighted vs. unweighted (ave. clients)			0.98	0.98	0.99	0.98
Corr: weighted vs. unweighted (MF clients)			0.98	0.98	0.98	0.99

Notes: The top portion of the table reports various summary statistics for measures of the fractions of dealers changing their securities-financing terms in each quarter, as constructed from SCOOS responses. The bottom portion shows the correlation between the various measures. "Ave." and "MF" refers to terms applied to "average" and "most favored" clients. Each statistic is computed within each asset class and then averaged across asset classes. Units are percentage of dealers changing terms in each quarter.

Table 3. Term variability across asset classes

	Financing spread	Haircut	Max. amount	Max. maturity
Agency MBS	0.13	0.11	0.12	0.11
IG corporate bonds#	0.16	0.12	0.11	0.13
HY corporate bonds	0.19	0.15	0.10	0.12
ABS#	0.19	0.15	0.13	0.11
CMBS#	0.21	0.18	0.15	0.14
Private MBS#	0.22	0.19	0.16	0.14
Equities	0.11	0.04	0.09	0.09

Notes: The table reports the standard deviation of the SCOOS-based indices of changes in the terms on securities funding, by asset class, using unweighted indices, averaged across average and most-favored clients. Units are the net percentage of dealers changing terms in each quarter. Data for asset classes marked with #'s begin in 2011:3; all others begin in 2010:2.

Table 4. Correlations of financing-term indices with other variables

A. By term type, aggregating across all asset classes

	SCOOS Terms				Liquidity				Volatility				Other Asset-Specific Market Conditions			GDP Forecast revisions
	Fin. Spread [1]	Haircut [2]	Max. mat. [3]	Max. amt. [4]	SCOOS Liquidity [5]	Amihud liquidity [6]	TED Spread [7]	5 Year On/Off [8]	Real. vol. [9]	VIX [10]	Swaption vol [11]	MOVE [12]	Returns [13]	Trading volume [14]	Issuance [15]	[16]
Fin. spread	1				-0.72***	0.26***	0.29***	0.48***	0.18***	0.36***	0.20***	0.13**	-0.26***	-0.09	0.02	-0.61%
Haircut	0.82***	1			-0.70***	0.20**	0.27***	0.45***	0.13**	0.27***	0.11*	0.07	-0.16**	-0.09	0.01	-0.71***
Max. amt.	0.72***	0.77***	1		-0.60***	0.20**	0.24***	0.39***	0.10	0.19***	0.03	-0.04	-0.20***	-0.04	0.04	-0.68***
Max. matur.	0.72***	0.81***	0.83***	1	-0.65***	0.31***	0.25***	0.39***	0.16**	0.25***	0.09	0.04	-0.17***	-0.06	-0.07	-0.69***

B. By asset class, aggregating across all terms

	Liquidity				Volatility				Other Asset-Specific Market Conditions			GDP Forecast revisions
	SCOOS Liquidity	Amihud liquidity	TED Spread	5 Year On/Off	Real. vol.	VIX	Swaption vol	MOVE	Returns	Trading volume	Issuance	
Agency MBS	-0.57***	-	0.12	0.38***	-0.01	0.22***	0.08	-0.00	0.10	-0.03	-0.14*	-0.59***
IG Corp	-0.70***	0.45***	0.28***	0.48***	0.41***	0.38***	0.19**	0.22***	-0.27***	0.35***	-0.05	-0.64***
HY Corp	-0.73***	0.42***	0.31***	0.52***	0.48***	0.27***	0.14*	0.07	-0.54***	-0.01	-0.20**	-0.64***
ABS	-0.53***	-	0.26***	0.39***	-0.08	0.29***	0.03	-0.00	0.10	-0.17**	-0.28***	-0.83***
CMBS	-0.71***	-	0.29***	0.46***	0.15*	0.29***	0.15*	0.06	-0.05	-0.22***	-0.16*	-0.77***
Priv. RMBS	-0.71***	-	0.38***	0.47***	-	0.25***	0.13	0.03	-	0.10	-0.17**	-0.72***
Equities	-	-	0.19**	0.33***	0.23***	0.25***	0.09	0.06	-0.29***	0.09	0.01	-0.53***

Notes: The tables show the correlations of quarterly changes in four types of securities financing terms (financing spreads, haircuts, maximum maturities, and maximum amounts), as measured using SCOOS diffusion indices, with various other data from the SCOOS and other sources. In the top panel, correlations are calculated treating each asset class-quarter as a separate observation. In the bottom panel, correlations are calculated treating each term-quarter as a separate observation. Shaded columns are time-series data matched as closely as possible to the SCOOS reporting dates; all other columns are matched to the SCOOS by both date and asset class. Asterisks indicate statistical significance at the 10%, 5%, and 1% level.

Table 4. Correlations of funding-term indices with other variables (continued)

A. By term type, aggregating across all asset classes (continued)

	Securities Financing					Dealer Condition					Other Financial Indicators					
	Funding Demand	"Securities in"(a)	Fails to deliv.	Triparty volume	Triparty haircuts	Excess CDS	Leverage	%Δ Book Equity	%Δ Assets	%Liq. Assets	3-Month Tbill	10 Year Treasury	CDX.IG	CDX.HY	GZ Bond Premium	Chicago FCI
	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	[29]	[30]	[31]	[32]
Fin. Rate	0.19***	-0.10	0.10	-0.02	0.04	0.23***	-0.11*	-0.20***	-0.35***	0.13**	-0.50***	-0.28***	0.55***	0.64***	0.43***	0.59***
Haircut	0.18***	-0.14*	-0.08	0.01	-0.03	0.25***	-0.00	-0.12*	-0.18***	0.33***	-0.62***	-0.41***	0.48***	0.63***	0.45***	0.61***
Max. amt.	0.08	-0.23***	0.02	-0.09	-0.02	0.08	-0.12**	0.05	-0.24***	0.24***	-0.57***	-0.29***	0.41***	0.59***	0.37***	0.49***
Max. matur.	0.03	-0.18**	-0.02	-0.02	-0.07	0.13**	-0.04	-0.08	-0.18***	0.24***	-0.57***	-0.34***	0.43***	0.59***	0.40***	0.57***

B. By asset class, aggregating across all terms (continued)

	Securities Financing					Dealer Condition					Other Financial Indicators					
	Funding Demand	"Securities in"(a)	Fails to deliv.	Triparty volume	Triparty haircuts	Excess CDS	Leverage	% Δ Book Equity	%Δ Assets	%Liq. Assets	3-Month Tbill	10 Year Treasury	CDX.IG	CDX.HY	GZ Bond Premium	Chicago FCI
Agency MBS	-0.35***	-0.24***	-0.13*	0.08	-0.08	0.09	-0.03	-0.15*	-0.21***	0.33***	-0.45***	-0.23***	0.36***	0.51***	0.39***	0.47***
IG Corp	0.09	-0.29***	0.14*	0.23***	-	0.04	-0.08	-0.13	-0.26***	0.16**	-0.49***	-0.27***	0.57***	0.67***	0.43***	0.66***
HY Corp	0.47***	-0.18*	-	-0.17**	-0.13	0.25***	-0.03	-0.20**	-0.30***	0.29***	-0.54***	-0.42***	0.57***	0.69***	0.47***	0.58***
ABS	0.64***	-0.24***	-	-0.19**	-0.08	0.14*	0.14	-0.00	-0.21**	0.12	-0.72***	-0.43***	0.51***	0.66***	0.42***	0.62***
CMBS	0.28**	-0.18*	-	-	-	0.28***	-0.04	-0.09	-0.19**	0.26***	-0.66***	-0.42***	0.51***	0.67***	0.41***	0.62***
Priv. RMBS	0.13	-0.05	-	0.05	0.04	0.31***	-0.04	-0.14	-0.23***	0.25***	-0.63***	-0.37**	0.49***	0.67***	0.41***	0.58***
Equities	-0.28***	0.17*	-	-0.22***	0.20**	0.09	-0.16**	-0.16**	-0.35***	0.08	-0.38***	-0.14*	0.30***	0.43***	0.26***	0.43***

Notes: The tables show the correlations of quarterly changes in four types of securities financing terms (financing spreads, haircuts, maximum maturities, and maximum amounts), as measured using SCOOS diffusion indices, with various other data from the SCOOS and other sources. In the top panel, correlations are calculated treating each asset class-quarter as a separate observation. In the bottom panel, correlations are calculated treating each term-quarter as a separate observation. Shaded columns are time-series data matched as closely as possible to the SCOOS reporting dates; all other columns are matched to the SCOOS by both date and asset class. Asterisks indicate statistical significance at the 10%, 5%, and 1% level.
(a) For the purposes of this table, the "Securities in" data from the FR-2004 report, which measures the gross amount of funding provided by primary dealers by asset class, is matched to the SCOOS asset class categories as follows. "Corporate bonds" from the FR-2004 are matched to both the IG and HY corporate bond SCOOS categories; "Asset-backed securities" and "Other" from the FR-2004, which are only reported together after 2013 and only separately reported after 2015, are combined and matched to the consumer ABS, CMBS, and private RMBS categories in the SCOOS. Agency MBS and equities from the FR-2004 are matched to their respective SCOOS categories.

Table 5. Correlation of liquidity index with other variables

	Liquidity			Volatility				Other Asset-Specific Market Conditions			GDP Forecast revisions
	Amihud liquidity [1]	TED Spread [2]	5 Year On/Off [3]	Real. vol. [4]	VIX [5]	Swaption vol [6]	MOVE [7[	Returns [8]	Trading volume [9]	Issuance [10]	[11]
Agency MBS	--	-0.23***	-0.47***	-0.29***	-0.39***	-0.41***	-0.26***	-0.00	0.01	-0.04	0.43***
IG Corp	-0.55***	-0.31***	-0.59***	-0.42***	-0.56***	-0.34***	-0.45***	0.34***	0.01	0.07	0.51***
HY Corp	-0.62***	-0.39***	-0.64***	-0.62***	-0.48***	-0.25***	-0.25***	0.66***	0.24***	--	0.50***
ABS	--	-0.30***	-0.47***	-0.03	-0.42***	-0.35***	-0.25***	-0.05	0.08	0.22***	0.50***
CMBS	--	-0.36***	-0.46***	-0.34***	-0.46***	-0.36***	-0.30***	0.29***	0.34***	-0.03	0.56***
Priv. RMBS	--	-0.37***	-0.53***	--	-0.34***	-0.44***	-0.23***	--	0.03	-0.01	0.59***

	Securities Financing					Dealer Condition					Other Financial Indicators					
	Funding Demand [12]	“Securities in”(a) [13]	Fails to deliv. [14]	Triparty volume [15]	Triparty haircuts [16]	Excess CDS [17]	Leverage [18]	% Δ Book Equity [19]	%Δ Assets [20]	%Liq. Assets [21]	3-Month Tbill [22]	10 Year Treasury [23]	CDX.IG [24]	CDX.HY [25]	GZ Bond Premium [26]	Chicago FCI [27]
Agency MBS	0.42***	0.08	0.18**	-0.15*	0.11	-0.17**	-0.05	0.44***	0.52***	-0.12	0.37***	0.22***	-0.64***	-0.68***	0.02	-0.61***
IG Corp	0.20**	0.42***	-0.07	-0.01	-0.10	-0.16*	-0.21**	0.31***	0.24***	-0.23***	0.22***	0.23***	-0.62***	-0.64***	-0.07	-0.67***
HY Corp	-0.31***	0.33***	--	0.12	0.05	-0.49***	-0.34***	0.32***	0.19**	-0.26***	0.34***	0.49***	-0.71***	-0.76***	0.00	-0.74***
ABS	-0.36***	0.09	--	-0.05	-0.00	-0.30***	-0.21**	0.28***	0.27***	-0.18**	0.43***	0.39***	-0.69***	-0.74***	-0.01	-0.69***
CMBS	0.08	0.20**	--	--	--	-0.47***	-0.35***	0.16*	0.16*	-0.28***	0.43***	0.41***	-0.72***	-0.83***	-0.01	-0.83***
Priv. RMBS	0.13	0.28***	--	-0.06	-0.04	-0.45***	-0.26***	0.26***	0.26***	-0.23**	0.49***	0.27***	-0.65***	-0.75***	0.15*	-0.72***

Notes: The table shows the correlations of our quarterly changes in market liquidity, as measured using SCOOS diffusion indices, with various other data from the SCOOS and other sources. Shaded columns are time-series data matched as closely as possible to the SCOOS reporting dates; all other columns are matched to the SCOOS by both date and asset class. Asterisks indicate statistical significance at the 10%, 5%, and 1% level.

(a) For the purposes of this table, the “Securities in” data from the FR-2004 report, which measures the gross amount of funding provided by primary dealers by asset class, is matched to the SCOOS asset class categories as follows. “Corporate bonds” from the FR-2004 are matched to both the IG and HY corporate bond SCOOS categories; “Asset-backed securities” and “Other” from the FR-2004, which are only reported together after 2013 and only separately reported after 2015, are combined and matched to the consumer ABS, CMBS, and private RMBS categories in the SCOOS. Agency MBS and equities from the FR-2004 are matched to their respective SCOOS categories.

Table 6. SCOOS market-liquidity index vs. other liquidity measures

	IG Corp. Bonds	HY Corp. Bonds	Pooled
Amihud liquidity *j,t*	-0.51***	-1.25***	-0.60***
	(0.13)	(0.44)	(0.12)
5y on/off spread *t*	-5.05***	-5.05***	-5.12***
	(1.42)	(1.52)	(1.09)
Realized vol *j,t*	0.25	-0.06	-0.17
	(1.02)	(1.14)	(0.75)
R^2	0.59	0.61	0.56
Adj. R^2	0.54	0.56	0.54
Obs	41	36	77

Notes: The table shows regressions of the SCOOS-based indices of market liquidity on various other measures, for the corporate-bond asset classes (the only asset classes where we can compute Amihud statistics from TRACE). Constant terms not shown. Standard errors in parentheses. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

Table 7. Regressions of funding-term indices on market conditions

A. Dependent variable: Financing Spread Index

	By Asset Class (j)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand j,t	-0.01 (0.13)	0.04 (0.19)	0.53** (0.20)	0.35 (0.27)	0.27* (0.14)	0.32*** (0.15)	-0.05 (0.09)	0.22*** (0.08)	0.24*** (0.08)	0.16*** (0.06)	0.15*** (0.06)
Liquidity j,t	-0.42* (0.24)	-0.36* (0.19)	-0.56*** (0.14)	-0.15 (0.13)	-0.50** (0.21)	-0.50*** (0.18)	--	-0.42*** (0.11)	-0.43*** (0.10)	-0.28*** (0.06)	-0.29*** (0.05)
Realized vol j,t	-1.82 (1.72)	0.98 (0.73)	-0.24 (1.18)	-3.68 (4.43)	-2.30 (1.49)	--	0.12 (0.21)	-0.13 (0.49)	--	-0.16 (0.43)	--
%Δ dealer equity t	0.60 (1.19)	-0.17 (1.36)	-1.02 (1.91)	-4.34** (1.92)	-3.92** (1.77)	-5.97*** (1.79)	-2.45 (1.57)	-1.63 (1.32)	-2.26* (1.27)	--	--
CDX HY t	0.04 (0.04)	0.07 (0.05)	0.01 (0.06)	0.01 (0.06)	-0.06 (0.07)	-0.05 (0.07)	-0.01 (0.04)	0.02 (0.04)	0.01 (0.04)	--	--
VIX t	0.01 (0.18)	-0.11 (0.32)	0.11 (0.36)	0.67*** (0.23)	0.68*** (0.17)	0.52 (0.39)	0.30 (0.21)	0.17 (0.17)	0.21 (0.18)	--	--
10Y swaption vol t	0.13 (0.25)	0.13 (0.27)	0.00 (0.25)	-0.39 (0.28)	-0.36 (0.37)	-0.64 (0.47)	-0.03 (0.24)	-0.04 (0.23)	-0.11 (0.24)	--	--
T bill rate t	-0.03 (0.11)	-0.07 (0.10)	-0.09 (0.08)	-0.29* (0.16)	-0.30** (0.13)	-0.28** (0.12)	-0.25*** (0.08)	-0.15** (0.07)	-0.17** (0.08)	--	--
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.31	0.53	0.73	0.65	0.70	0.69	0.34	0.62	0.64	0.82	0.83
Obs	41	41	36	36	36	36	41	190	226	190	226

Notes: The table shows regression results of indices of changes in financing spreads from the SCOOS on various explanatory variables. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

B. Dependent variable: Haircut Index

	By Asset Class (j)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand j,t	-0.25***	0.10	0.20	0.29*	0.07	0.04	0.00	0.05	0.05	0.04	0.02
	(0.08)	(0.12)	(0.16)	(0.15)	(0.12)	(0.10)	(0.03)	(0.05)	(0.06)	(0.06)	(0.05)
Liquidity j,t	-0.22	-0.33***	-0.52***	-0.02	-0.42***	-0.32***	--	-0.31***	-0.31***	-0.18***	-0.18***
	(0.18)	(0.10)	(0.15)	(0.08)	(0.14)	(0.11)		(0.07)	(0.06)	(0.06)	(0.06)
Realized vol j,t	-0.14	-0.31	-0.87	2.72	-0.73	--	0.03	-0.20	--	-0.45	--
	(1.60)	(0.66)	(0.81)	(2.20)	(1.55)		(0.09)	(0.49)		(0.49)	
%Δ dealer equity t	0.22	-0.99	0.14	-2.83**	-2.48**	-4.67***	-0.93*	-1.28	-1.79**	--	--
	(1.19)	(0.77)	(1.39)	(1.11)	(1.30)	(1.30)	(0.54)	(0.77)	(0.78)		
CDX HY t	0.03	0.04	0.06	0.02	-0.06	-0.05	0.01	0.02	0.01	--	--
	(0.04)	(0.02)	(0.04)	(0.04)	(0.06)	(0.04)	(0.01)	(0.02)	(0.02)		
VIX t	0.08	-0.12	-0.37*	0.27	0.23	0.49**	0.06	-0.03	-0.04	--	--
	(0.20)	(0.13)	(0.19)	(0.31)	(0.40)	(0.20)	(0.07)	(0.17)	(0.12)		
10Y swaption vol t	-0.20	-0.06	-0.06	-0.39**	-0.31	-0.56	-0.11	-0.17	-0.22*	--	--
	(0.18)	(0.17)	(0.20)	(0.18)	(0.29)	(0.35)	(0.07)	(0.12)	(0.13)		
T bill rate t	-0.15**	-0.19***	-0.13	-0.35***	-0.37***	-0.43***	-0.05	-0.25***	-0.28***	--	--
	(0.07)	(0.04)	(0.08)	(0.09)	(0.12)	(0.09)	(0.03)	(0.05)	(0.05)		
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.56	0.77	0.74	0.80	0.71	0.72	0.30	0.70	0.71	0.78	0.80
Obs	41	41	36	36	36	36	41	190	226	190	226

Notes: The table shows regression results of indices of changes in haircuts from the SCOOS on various explanatory variables. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

C. Dependent variable: Maximum Amounts Index

	By Asset Class (j)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand j,t	-0.22** (0.10)	-0.18 (0.11)	0.01 (0.14)	0.12 (0.19)	0.06 (0.16)	0.02 (0.08)	-0.03 (0.08)	-0.05 (0.07)	-0.05 (0.06)	-0.05 (0.06)	-0.07 (0.05)
Liquidity j,t	-0.12 (0.20)	-0.33** (0.14)	-0.19** (0.08)	0.07 (0.07)	-0.18 (0.12)	-0.32*** (0.11)	--	-0.19** (0.07)	-0.21*** (0.06)	-0.14*** (0.07)	-0.17*** (0.06)
Realized vol j,t	-3.07* (1.78)	-0.39 (0.64)	-1.85*** (0.64)	-2.36 (2.95)	-4.31*** (1.36)	--	0.14 (0.20)	-1.28** (0.51)	--	-0.78** (0.47)	--
%Δ dealer equity t	0.44 (1.49)	1.03 (0.80)	0.53 (0.95)	-0.37 (0.82)	-1.01 (1.18)	0.47 (1.25)	-2.76** (1.36)	0.11 (0.82)	0.16 (0.88)	--	--
CDX HY t	0.05 (0.03)	0.07* (0.03)	0.12*** (0.03)	0.07 (0.04)	0.04 (0.06)	0.07 (0.05)	-0.01 (0.03)	0.06*** (0.02)	0.05*** (0.02)	--	--
VIX t	-0.11 (0.16)	-0.34 (0.21)	-0.10 (0.19)	0.02 (0.17)	0.19 (0.39)	-0.39* (0.22)	0.09 (0.16)	-0.14 (0.14)	-0.24** (0.17)	--	--
10Y swaption vol t	-0.08 (0.22)	-0.17 (0.15)	-0.03 (0.15)	-0.24 (0.21)	-0.18 (0.30)	-0.45 (0.31)	0.06 (0.23)	-0.15 (0.13)	-0.23** (0.14)	--	--
T bill rate t	-0.13* (0.08)	-0.11* (0.06)	-0.10* (0.05)	-0.26*** (0.08)	-0.28** (0.12)	-0.15** (0.07)	-0.16** (0.08)	-0.18*** (0.05)	-0.17*** (0.05)	--	--
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.41	0.63	0.62	0.66	0.65	0.70	0.22	0.56	0.58	0.75	0.77
Obs	41	41	36	36	36	36	41	190	226	190	226

Notes: The table shows regression results of indices of changes in haircuts from the SCOOS on various explanatory variables. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

D. Dependent variable: Maximum Maturity Index

	By Asset Class (*j*)							**Pooled**			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand *j,t*	-0.12*	-0.11	0.01	0.15	0.00	-0.12	-0.13*	-0.05	-0.06	-0.01	0.04
	(0.07)	(0.12)	(0.14)	(0.14)	(0.13)	(0.08)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
Liquidity *j,t*	-0.28*	-0.46***	-0.21**	0.04	-0.27*	-0.21**	--	-0.25***	-0.24***	-0.21***	-0.21***
	(0.16)	(0.14)	(0.09)	(0.06)	(0.15)	(0.09)		(0.07)	(0.07)	(0.06)	(0.05)
Realized vol *j,t*	-2.93**	0.29	-0.61	-0.69	-2.18*	--	0.18	-0.32	--	-0.03	--
	(1.31)	(0.84)	(0.75)	(1.76)	(1.23)		(0.16)	(0.43)		(0.35)	
%Δ dealer equity *t*	-2.29**	1.09	-2.20*	-0.76	0.55	-0.43	-1.05	-0.76	-0.72	--	--
	(1.11)	(1.13)	(1.16)	(1.11)	(1.19)	(1.13)	(1.37)	(0.92)	(0.90)		
CDX HY *t*	-0.05	0.05	0.04	0.05	0.04	0.02	0.00	0.02	0.02	--	--
	(0.03)	(0.03)	(0.03)	(0.03)	(0.07)	(0.04)	(0.03)	(0.02)	(0.02)		
VIX *t*	0.35*	-0.25	-0.02	0.11	-0.26	0.12	0.03	-0.05	-0.04	--	--
	(0.18)	(0.23)	(0.16)	(0.12)	(0.38)	(0.28)	(0.19)	(0.14)	(0.14)		
10Y swaption vol *t*	-0.12	-0.26	-0.19	-0.17	0.09	-0.4	-0.04	-0.16*	-0.20**	--	--
	(0.18)	(0.25)	(0.18)	(0.20)	(0.26)	(0.27)	(0.25)	(0.15)	(0.15)		
T bill rate *t*	-0.20***	-0.12**	-0.21***	-0.24***	-0.19*	-0.23***	-0.11	-0.20***	-0.20***	--	--
	(0.06)	(0.06)	(0.05)	(0.07)	(0.10)	(0.07)	(0.07)	(0.04)	(0.04)		
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.52	0.65	0.66	0.64	0.63	0.65	0.11	0.60	0.62	0.75	0.78
Obs	41	41	36	36	36	36	41	190	226	190	226

Notes: The table shows regression results of indices of changes in haircuts from the SCOOS on various explanatory variables. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

Table 8. Standardized regression coefficients in pooled model

	Fin. Spreads	Haircuts	Max. Amounts	Max. Maturity
Demand	**0.18**	0.05	-0.06	-0.05
Liquidity	**-0.50**	**-0.45**	**-0.32**	**-0.42**
Real. vol.	-0.01	-0.02	**-0.18**	-0.04
%Δ dealer equity	-0.15	-0.15	0.01	-0.10
CDX HY	0.09	0.09	**0.32**	0.12
VIX	0.08	-0.02	-0.10	-0.04
10Y Swaption vol	-0.02	-0.09	-0.09	-0.10
T bill rate	**-0.26**	**-0.50**	**-0.44**	**-0.46**
Adj. R^2	0.62	0.70	0.56	0.60

Notes: The table reports standardized coefficients from the regressions in Table 6, using the pooled specification with five asset classes and time-series control variables. Standardized coefficients are defined as the number of standard deviations that the dependent variable (the four financing terms indicated) changes in response to a one-standard-deviation change in the independent variable. Coefficients in boldface are those that are statistically significant at the 5% confidence level. Each regression has a sample size of 190 observations and includes asset-class fixed effects.

Table 9. Standardized regression coefficients in pooled model, excluding COVID-19 observations

	Fin. Spreads	Haircuts	Max. Amounts	Max. Maturity
Demand	**0.16**	0.02	**-0.20**	**-0.16**
Liquidity	**-0.53**	**-0.55**	**-0.37**	**-0.46**
Real. Vol.	-0.00	-0.01	**-0.21**	-0.06
%Δ Dealer Equity	-0.21	**-0.25**	-0.06	-0.18
CDX HY	0.01	-0.02	0.13	-0.01
VIX	0.11	0.01	-0.08	-0.00
Swaption vol	-0.00	-0.10	-0.07	-0.09
T Bill rate	-0.08	**-0.24**	-0.02	-0.17
Adj. R^2	0.44	0.43	0.23	0.35

Notes: The table reports standardized coefficients from the regressions using the pooled specification with five asset classes and time-series control variables (the analogue of the results in Table 6), excluding observations from Q2 2020. Standardized coefficients are defined as the number of standard deviations that the dependent variable (the four financing terms indicated) changes in response to a one-standard-deviation change in the independent variable. Coefficients in boldface are those that are statistically significant at the 5% confidence level. Each regression has a sample size of 185 observations and includes asset-class fixed effects.

Table 10. Correlation of the regression time effects with other time series

	Financing Spread Time Dummies		Haircuts Time Dummies		Max Mat Time Dummies		Max Amt. Time Dummies	
	5 asset classes	6 asset classes	5 asset classes	6 asset classes	5 asset classes	6 asset classes	5 asset classes	6 asset classes
SCOOS Liquidity (Avg)	-0.70	-0.69	-0.72	-0.71	-0.56	-0.53	-0.58	-0.51
Demand (Avg)	0.07	0.09	0.23	0.25	0.10	0.15	0.20	0.24
Real. Vol.	0.48	0.45	0.51	0.47	0.27	0.29	0.29	0.19
%Δ dealer equity	-0.16	-0.19	-0.05	-0.08	-0.02	0.01	0.05	0.07
CDX HY	0.61	0.60	-0.69	-0.67	0.55	0.55	0.61	0.56
VIX	0.37	0.34	0.30	0.28	0.19	0.20	0.21	0.13
10Y Swaption vol	0.22	0.20	0.07	0.07	-0.05	-0.07	-0.05	-0.13
T bill rate	-0.45	-0.45	-0.73	-0.73	-0.61	-0.63	-0.66	-0.65

Notes: The table shows the univariate correlations between the coefficients on the time dummies with various other time series in each of the pooled regressions of Table 5 that contain time fixed effecgs. "Avg" indicates data that are averaged across asset classes to construct a single series.

Table 11. Self-reported reasons for changing terms to various counterparties

	Counterparty risk	Market liquidity	Risk willingness	Int. treas chrges	Capital avail	Competition	Market conventions
Hedge funds	0.13	0.20	0.12	0.07	0.12	0.28	0.09
Insurance cos.	0.14	0.18	0.06	0.12	0.16	0.21	0.14
Nonfin. corps.	0.14	0.18	0.14	0.12	0.09	0.23	0.11
Mutual funds, etc.	0.06	0.20	0.10	0.06	0.14	0.35	0.09
REITs	0.19	0.21	0.14	0.04	0.11	0.25	0.06
Sep'ly mangd accts	0.06	0.20	0.08	0.05	0.11	0.38	0.11
Average:	0.12	0.20	0.11	0.08	0.12	0.28	0.10

Notes: The table shows the relative frequencies with which dealers report each reason for tightening or easing terms on securities financing and derivatives transactions either as "very important" or as among the three most-important reasons, for each counterparty type. Each row sums to 1.00. Hedge funds, insurance companies, and nonfinancial corporations are reported for 2010:2 – 2020:2; all other series begin in 2011:3.

Table 12. Effects of funding-term indices on market liquidity

	Excluding Private MBS	Including Private MBS
Fin. Spreads $_{j,t}$	-0.97	-0.61
	(0.76)	(0.45)
Max. amounts $_{j,t}$	0.13	-0.19
	(0.62)	(0.40)
Wald $\chi^2(2)$	9.9***	13.6***
Control variables	Yes	Yes
Asset class F.E.	Yes	Yes
R^2	0.65	0.72
Obs.	190	226

Notes: The Table shows the results of panel 2-stage least-squares regressions of the SCOOS liquidity index on the indices of changes in funding terms, where the terms indices are instrumented with net percentages of dealers reporting changing terms because of market conventions. The regressions pool data across asset classes and exclude equities, which have no liquidity index. The vector of control variables is described in the text. Robust standard errors in parentheses.

Table 13. Effects of funding-term indices on asset returns

	Excluding Equities	Including Equities
Fin. Spreads *j,t*	0.9	-0.9
	(20.0)	(10.5)
Max. amounts *j,t*	-11.8	-9.4
	(13.5)	(10.2)
Wald $\chi^2(2)$	5.2*	2.6
Control variables	Yes	Yes
Asset class F.E.	Yes	Yes
R^2		
Obs.	190	231

Notes: The Table shows the results of panel 2-stage least-squares regressions of quarterly asset returns on the indices of changes in funding terms, where the terms indices are instrumented with net percentages of dealers reporting changing terms because of market conventions. The regressions pool data across asset classes and exclude private-label MBS, which have no returns data. The vector of control variables is described in the text. Robust standard errors in parentheses.

Table 14. Funding induced volatility across portfolios

		Portfolio Weights						Volatility from funding terms
		Agency MBS	IG Corp	HY Corp	ABS	CMBS	Equities	
Agency MBS only		1						0.91%
IG corp only			1					0.78%
HY corp only				1				1.96%
ABS only					1			0.89%
CMBS only						1		1.25%
Equities only							1	0.12%
Equally weighted	Incl. CMBS & Equities	0.17	0.17	0.17	0.17	0.17	0.17	0.38%
	Excl. CMBS & Equities	0.25	0.25	0.25	0.25			0.74%
Min. vol from funding terms	Incl. CMBS & Equities	0.00	0.06	0.00	0.00	0.03	0.91	0.09%
	Excl. CMBS & Equities	0.00	0.58	0.09	0.34			0.33%

Notes: The Table shows the contribution of funding terms to the standard deviation of quarterly returns on variously weighted portfolios of asset classes. The contribution of funding terms to the volatility of each asset class is calculated by regressing security returns on indices of changes in funding terms (and controls), multiplying the resulting coefficients by respective funding-term-index variances and covariances, and applying specified portfolio weights. Regressions are estimated by two-stage least squares using the fraction of dealers reporting changing terms because of market conventions to various counterparties as instruments. In the first stage, F statistics indicate possible weak instruments for the equations involving CMBS and equities.

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Appendix. Additional statistics and alternative specifications

Table A.1 reports a breakdown of the correlations among our indices of changes in financing terms into their cross-sectional and time-series components. Tables A.2 through A.4 report the results of various alternative specifications of the baseline regressions in Table 5 of the main text. Table A.2 drops the last quarter of the sample, Q2 2020, which includes the extreme observations associated with the onset of the COVID-19 crisis. Table A.3 considers alternative measures of dealer condition, in place of the change in equity used in our baseline specification, splitting the sample across more-liquid and less-liquid securities. Table A.4 considers an alternative set of time-series control variables for risk and volatility in these regressions and drops the Treasury bill rate as a control. Finally, Table A.5 reports the results of our asset-return regressions (Table 13 in the paper), when we drop the Q2 2020 observations.

A.1 Comovement in funding-term indices across asset classes and over time

Between asset classes (Cross-sectional)

	Financing spreads	Haircuts	Maximum amounts	Maximum maturities
Standard deviation	0.08	0.07	0.06	0.06
Correlation with:				
Financing spreads	1			
Haircuts	0.62	1		
Maximum amounts	0.39	0.46	1	
Maximum maturities	0.38	0.53	0.53	1

Within asset classes (Time-series)

	Financing spreads	Haircuts	Maximum amounts	Maximum maturities
Standard deviation	0.17	0.14	0.12	0.12
Correlation with:				
Financing spreads	1			
Haircuts	0.82	1		
Maximum amounts	0.71	0.77	1	
Maximum maturities	0.72	0.81	0.84	1

Notes: The tables show the between- and within-group standard deviations of and correlations between our indices of dealers' reported changes in funding terms. The "between asset class" statistics de-mean the indices by quarter, while the "within asset class" statistics de-mean by asset class.

A.2 Regressions of financing-term indices on market conditions, excluding Q2 2020

A. Dependent variable: financing spread index

	By Asset Class (*j*)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand *j,t*	0.09 (0.12)	-0.05 (0.19)	0.55** (0.22)	0.31 (0.29)	0.26* (0.13)	0.31** (0.15)	-0.03 (0.09)	0.19** (0.07)	0.22*** (0.08)	0.11* (0.06)	0.11* (0.05)
Liquidity *j,t*	-0.53** (0.23)	-0.30 (0.19)	-0.56*** (0.15)	-0.17 (0.14)	-0.50** (0.21)	-0.49** (0.18)	--	-0.41*** (0.11)	-0.41*** (0.10)	-0.22*** (0.05)	-0.23*** (0.05)
Realized vol *j,t*	-3.08* (1.63)	0.95 (0.63)	-0.17 (1.24)	-2.96 (4.31)	-2.16 (1.53)	--	0.10 (0.19)	-0.04 (0.51)	--	0.19 (0.53)	--
%Δ dealer equity *t*	0.27 (1.83)	-0.47 (1.31)	-0.99 (1.89)	-4.46** (2.00)	-4.00** (1.83)	-6.03*** (1.84)	-2.61* (1.54)	-1.81** (1.31)	-2.43* (1.29)	--	--
CDX HY *t*	-0.01 (0.05)	0.06 (0.05)	0.02 (0.05)	-0.01 (0.08)	-0.07 (0.07)	-0.06 (0.07)	-0.03 (0.04)	0.00 (0.04)	0.00 (0.04)	--	--
VIX *t*	0.10 (0.19)	-0.03 (0.31)	0.09 (0.35)	0.67** (0.25)	0.69*** (0.18)	0.53 (0.40)	0.34 (0.23)	0.19 (0.20)	0.24* (0.21)	--	--
10Y swaption vol *t*	0.24 (0.26)	0.18 (0.27)	-0.02 (0.26)	-0.38 (0.29)	-0.35 (0.38)	-0.61 (0.46)	-0.01 (0.24)	0.00 (0.23)	-0.07 (0.24)	--	--
T bill rate *t*	0.14 (0.13)	0.02 (0.14)	-0.12 (0.13)	-0.23 (0.19)	-0.26 (0.16)	-0.24 (0.16)	-0.15 (0.09)	-0.07 (0.12)	-0.10 (0.12)	--	--
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.20	0.36	0.61	0.38	0.49	0.51	0.04	0.44	0.46	0.74	0.75
Obs	40	40	35	35	35	35	40	185	220	185	220

Notes: The table shows regression results of indices of changes in financing spreads from the SCOOS on various explanatory variables, excluding observations from the second quarter of 2020. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

B. Dependent variable: Haircut index

	By Asset Class (*j*)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand $_{j,t}$	-0.15** (0.08)	0.07 (0.12)	0.16 (0.18)	0.22 (0.15)	0.03 (0.10)	0.03 (0.09)	0.02 (0.03)	0.01 (0.05)	0.02 (0.05)	-0.01 (0.06)	-0.02 (0.05)
Liquidity $_{j,t}$	-0.31* (0.16)	-0.31*** (0.10)	-0.52*** (0.15)	-0.06 (0.07)	-0.41*** (0.14)	-0.30** (0.12)	--	-0.29*** (0.06)	-0.28*** (0.06)	-0.11* (0.06)	-0.10* (0.06)
Realized vol $_{j,t}$	-1.31 (1.93)	-0.32 (0.69)	-1.01 (0.81)	4.19* (2.11)	-0.30 (1.60)	--	0.02 (0.05)	-0.05 (0.56)	--	-0.05 (0.83)	--
%Δ dealer equity $_t$	-0.08 (1.05)	-1.08 (0.75)	0.07 (1.37)	-3.06** (1.14)	-2.75** (1.31)	-4.76*** (1.33)	-1.09** (0.47)	-1.51** (0.75)	-2.01** (0.79)	--	--
CDX HY $_t$	-0.02 (0.04)	0.03 (0.02)	0.05 (0.03)	-0.02 (0.04)	-0.09 (0.06)	-0.06 (0.05)	-0.01 (0.01)	0.00 (0.02)	-0.01 (0.02)	--	--
VIX $_t$	0.16 (0.15)	-0.10 (0.14)	-0.35* (0.18)	0.27 (0.27)	0.25 (0.33)	0.49** (0.22)	0.10 (0.07)	0.01 (0.13)	0.08 (0.11)	--	--
10Y swaption vol $_t$	-0.10 (0.19)	-0.05 (0.17)	-0.02 (0.21)	-0.38* (0.20)	-0.27 (0.31)	-0.51 (0.36)	-0.09 (0.07)	-0.13 (0.13)	-0.17 (0.14)	--	--
T bill rate $_t$	0.01 (0.08)	-0.16*** (0.05)	-0.07 (0.11)	-0.24** (0.11)	-0.27* (0.13)	-0.39*** (0.13)	0.03 (0.03)	-0.15** (0.06)	-0.19*** (0.06)	--	--
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.28	0.57	0.56	0.44	0.40	0.44	0.26	0.43	0.43	0.57	0.61
Obs	40	40	35	35	35	35	40	185	220	185	220

Notes: The table shows regression results of indices of changes in haircuts from the SCOOS on various explanatory variables, excluding observations from the second quarter of 2020. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

C. Dependent variable: maximum amount index

	By Asset Class (*j*)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand *j,t*	-0.09 (0.08)	-0.27** (0.12)	-0.07 (0.12)	-0.01 (0.12)	-0.01 (0.14)	0.00 (0.08)	0.00 (0.09)	-0.12** (0.05)	-0.10* (0.05)	-0.10* (0.05)	-0.11*** (0.04)
Liquidity *j,t*	-0.26 (0.17)	-0.28** (0.12)	-0.20** (0.08)	0.00 (0.05)	-0.15 (0.10)	-0.28** (0.11)	--	-0.15** (0.06)	-0.16*** (0.05)	-0.05 (0.05)	-0.09* (0.05)
Realized vol *j,t*	-4.68*** (1.50)	-0.41 (0.42)	-2.11*** (0.57)	0.56 (1.52)	-3.50*** (1.01)	--	0.12 (0.16)	-1.11** (0.43)	--	0.06 (0.36)	--
%Δ dealer equity *t*	0.02 (1.30)	0.71 (0.64)	0.40 (0.87)	-0.83 (0.56)	-1.52 (1.01)	0.28 (1.24)	-2.97** (1.26)	-0.27 (0.64)	-0.21 (0.77)	--	--
CDX HY *t*	-0.02 (0.03)	0.05 (0.04)	0.10*** (0.03)	-0.01 (0.02)	-0.02 (0.05)	0.05 (0.05)	-0.03 (0.03)	0.02 (0.02)	0.02 (0.02)	--	--
VIX *t*	0.01 (0.19)	-0.25 (0.19)	-0.05 (0.20)	0.04 (0.10)	0.21 (0.26)	-0.38* (0.18)	0.14 (0.16)	-0.08 (0.10)	-0.17** (0.12)	--	--
10Y swaption vol *t*	0.06 (0.24)	-0.12 (0.14)	0.04 (0.15)	-0.22 (0.16)	-0.10 (0.24)	-0.35 (0.30)	0.09 (0.24)	-0.07 (0.12)	-0.14* (0.13)	--	--
T bill rate *t*	0.09 (0.07)	-0.01 (0.06)	0.00 (0.07)	-0.04 (0.06)	-0.08 (0.09)	-0.05 (0.08)	-0.05 (0.09)	-0.01 (0.04)	-0.01 (0.05)	--	--
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.26	0.53	0.41	-0.15	0.21	0.25	0.10	0.23	0.23	0.50	0.52
Obs	40	40	35	35	35	35	40	185	220	185	220

Notes: The table shows regression results of indices of changes in maximum amounts from the SCOOS on various explanatory variables, excluding observations from the second quarter of 2020. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "six asset classes" columns exclude data on private RMBS, while the "five asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

D. Dependent variable: maximum maturity index

	By Asset Class (*j*)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand *j,t*	-0.06 (0.08)	-0.20 (0.12)	-0.05 (0.14)	0.09 (0.15)	-0.07 (0.10)	-0.13 (0.08)	-0.09 (0.08)	-0.12** (0.05)	-0.12*** (0.04)	-0.09 (0.05)	-0.10** (0.04)
Liquidity *j,t*	-0.34** (0.15)	-0.40*** (0.14)	-0.21** (0.09)	0.01 (0.05)	-0.25* (0.13)	-0.17* (0.09)	--	-0.22*** (0.06)	-0.20*** (0.06)	-0.15*** (0.05)	-0.15*** (0.05)
Realized vol *j,t*	-3.70** (1.37)	0.27 (0.62)	-0.79 (0.71)	0.55 (1.68)	-1.50 (1.21)	--	0.16 (0.11)	-0.35 (0.46)	--	0.24 (0.37)	--
%Δ dealer equity *t*	-2.49** (1.07)	0.79 (1.03)	-2.29** (1.09)	-0.95 (1.17)	0.13 (1.16)	-0.66 (1.15)	-1.29 (1.30)	-1.01 (0.84)	-0.99 (0.85)	--	--
CDX HY *t*	-0.08** (0.03)	0.03 (0.04)	0.02 (0.03)	0.01 (0.03)	-0.01 (0.06)	0.00 (0.04)	-0.03 (0.04)	0.00 (0.02)	0.00 (0.02)	--	--
VIX *t*	0.40** (0.19)	-0.17 (0.23)	0.02 (0.15)	0.12 (0.09)	-0.23 (0.27)	0.14 (0.23)	0.08 (0.21)	0.00 (0.12)	0.01 (0.11)	--	--
10Y swaption vol *t*	-0.05 (0.20)	-0.21 (0.26)	-0.14 (0.19)	-0.16 (0.21)	0.16 (0.25)	-0.28 (0.26)	0.00 (0.26)	-0.10 (0.15)	-0.14* (0.14)	--	--
T bill rate *t*	-0.10 (0.08)	-0.03 (0.07)	-0.13 (0.08)	-0.15* (0.09)	-0.03 (0.08)	-0.12 (0.08)	0.03 (0.07)	-0.09* (0.05)	-0.10* (0.05)	--	--
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.42	0.49	0.44	-0.05	0.26	0.21	-0.06	0.35	0.35	0.57	0.60
Obs	40	40	35	35	35	35	40	185	220	185	220

Notes: The table shows regression results of indices of changes in maximum maturities from the SCOOS on various explanatory variables, excluding observations from the second quarter of 2020. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

A.3 Effect of dealer condition on term indices, using alternative measures

Measure of dealer condition		More-liquid bonds (Agency MBS, Corporates)				Less-liquid bonds (ABS, CMBS, private RMBS)			
		Spreads	Haircuts	Max. Amts.	Max. Matur.	Spreads	Haircuts	Max. Amts.	Max. Matur.
%Δ Equity (Baseline)	Full sample	-0.18 (0.88)	-0.54 (0.66)	0.56 (0.62)	-0.96 (0.73)	-4.77*** (1.06)	-3.25*** (0.79)	-0.34 (0.79)	-0.24 (0.72)
	Ex. Q2 2022	-0.32 (0.87)	-0.69 (0.66)	0.37 (0.58)	-1.11 (0.69)	-4.89*** (1.08)	-3.43*** (0.79)	-0.71 (0.70)	-0.51 (0.70)
Leverage ratio	Full sample	-4.52 (3.42)	5.71** (2.87)	-3.37 (2.74)	3.66 (2.58)	-2.04 (5.60)	14.78*** (3.93)	5.11 (3.49)	6.91** (3.19)
	Ex. Q2 2022	-4.04 (3.35)	6.26** (2.82)	-2.66 (2.56)	4.20 (2.59)	-2.04 (5.56)	14.90*** (3.77)	5.35* (2.95)	7.16** (2.95)
%Δ Assets	Full sample	-0.71 (0.57)	0.54 (0.33)	-0.25 (0.39)	0.07 (0.39)	-2.52*** (0.71)	0.68 (0.51)	0.59 (0.40)	0.86* (0.44)
	Ex. Q2 2022	-0.71 (0.54)	0.53 (0.31)	-0.25 (0.37)	0.08 (0.39)	-2.57*** (0.71)	0.61 (0.47)	0.43 (0.34)	0.75* (0.38)
Excess CDS spread	Full sample	-4.17 (5.81)	2.35 (4.39)	-11.52** (4.98)	-6.55 (4.00)	16.42** (6.67)	19.62*** (6.20)	-4.49 (6.46)	0.81 (4.94)
	Ex. Q2 2022	-1.83 (5.87)	5.06 (4.36)	-8.44** (4.13)	-3.86 (3.94)	18.73** (7.56)	23.56*** (7.20)	2.18 (5.00)	6.10 (4.88)

Notes: The table shows regression results of indices of changes in the diffusion indices of funding terms from the SCOOS on various explanatory variables, pooling across less-liquid and more-liquid asset classes, both including and excluding observation from Q2 2020. In each set of rows, changes in dealer condition are measured using a different explanatory variable. Variable construction is described in the text. Not shown, each regression also includes asset-class-specific indices of funding demand and liquidity, asset class fixed effects, and quarterly changes in the high-yield CDX index, the VIX, the 10-year swaption volatility, and the 3-month TBill rate. Heteroskedasticity-robust standard errors in parentheses. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels. Sample sizes are: more-liquid bonds, full sample, 118; less-liquid bonds, full sample, 108; more-liquid bonds, excluding Q2 2022, 115; less-liquid bonds, excluding Q2 2022, 105.

A.4 Regressions of financing terms on market conditions, using alternative control variables

A. Dependent variable: financing spread index

	By Asset Class (*j*)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand *j,t*	0.02 (0.11)	0.10 (0.17)	0.56*** (0.18)	0.67*** (0.17)	0.40*** (0.13)	0.28* (0.14)	-0.12 (0.10)	0.31*** (0.09)	0.31*** (0.09)	0.16** (0.06)	0.15** (0.06)
Liquidity *j,t*	-0.67*** (0.20)	-0.40** (0.15)	-0.56*** (0.08)	-0.16 (0.12)	-0.54*** (0.10)	-0.55*** (0.13)	--	-0.50*** (0.08)	-0.52*** (0.08)	-0.28*** (0.06)	-0.29*** (0.05)
Realized vol *j,t*	-1.67 (1.86)	1.84 (0.97)	-0.39 (0.86)	1.74 (4.40)	-0.88 (1.68)	--	0.16 (0.26)	0.35 (0.38)	--	-0.16 (0.43)	--
%Δ Dealer Assets *t*	1.08 (1.36)	-1.11 (0.92)	-1.19 (0.85)	-2.45* (1.33)	-1.36 (1.30)	-2.67** (1.21)	-1.85** (0.88)	-1.35* (0.74)	-1.54* (0.77)	--	--
CDX IG *t*	-0.06 (0.18)	0.25 (0.18)	0.18 (0.14)	0.32** (0.16)	0.13 (0.18)	0.06 (0.20)	-0.01 (0.17)	0.13 (0.11)	0.12 (0.11)	--	--
VIX *t*	0.21 (0.17)	-0.03 (0.33)	0.12 (0.30)	0.52* (0.27)	0.31 (0.33)	0.39 (0.38)	0.51** (0.23)	0.19 (0.17)	0.22 (0.17)	--	--
MOVE *t*	-0.03 (0.16)	-0.15 (0.14)	-0.14 (0.11)	-0.33** (0.13)	-0.17 (0.16)	-0.29 (0.21)	-0.16 (0.13)	-0.16* (0.09)	-0.17* (0.10)	--	--
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.30	0.56	0.76	0.67	0.68	0.64	0.17	0.62	0.63	0.74	0.75
Obs	41	41	36	36	36	36	41	190	226	185	220

Notes: The table shows regression results of indices of changes in financing spreads from the SCOOS on various explanatory variables, using an alternative set of regressors to the baseline model reported in the text. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels..

B. Dependent variable: Haircut index

	By Asset Class (*j*)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand *j,t*	-0.19*	0.34**	0.43**	0.79***	0.51***	0.25*	-0.02	0.26**	0.27***	0.04	-0.02
	(0.10)	(0.14)	(0.19)	(0.20)	(0.15)	(0.15)	(0.03)	(0.11)	(0.11)	(0.06)	(0.05)
Liquidity *j,t*	-0.54***	-0.50***	-0.58***	-0.09	-0.53***	-0.57***	--	-0.48***	-0.51***	-0.18***	-0.18***
	(0.12)	(0.12)	(0.13)	(0.09)	(0.10)	(0.14)		(0.08)	(0.08)	(0.06)	(0.06)
Realized vol *j,t*	0.46	0.29	-0.09	5.47	0.39	--	0.05	0.49	--	-0.45	--
	(2.00)	(0.99)	(0.93)	(3.72)	(2.16)		(0.08)	(0.52)		(0.49)	
%Δ Dealer Assets *t*	1.89***	0.02	0.45	0.16	1.95*	0.34	-0.70**	0.42	0.43	--	--
	(0.58)	(0.66)	(0.68)	(0.69)	(1.11)	(0.95)	(0.33)	(0.38)	(0.39)		
CDX IG *t*	-0.01	0.10	0.14	0.29**	0.12	-0.03	0.06	0.09	0.08	--	--
	(0.17)	(0.10)	(0.15)	(0.14)	(0.17)	(0.17)	(0.05)	(0.10)	(0.10)		
VIX *t*	0.22	-0.22	-0.35	0.13	-0.20	0.21	0.10	-0.09	-0.04	--	--
	(0.23)	(0.23)	(0.22)	(0.44)	(0.49)	(0.33)	(0.11)	(0.23)	(0.23)		
MOVE *t*	-0.22*	-0.10	-0.18	-0.24*	-0.07	-0.20	-0.09*	-0.16	-0.16	--	--
	(0.17)	(0.14)	(0.16)	(0.13)	(0.17)	(0.18)	(0.06)	(0.12)	(0.12)		
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.45	0.64	0.70	0.64	0.64	0.53	0.24	0.56	0.57	0.57	0.61
Obs	41	41	36	36	36	36	41	190	226	185	220

Notes: The table shows regression results of indices of changes in haircuts from the SCOOS on various explanatory variables, using an alternative set of regressors to the baseline model reported in the text. The first set of columns show separate regressions for each asset class, while the second set of columns. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

C. Dependent variable: maximum amounts

	By Asset Class (*j*)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand *j,t*	-0.17	0.00	0.22	0.64**	0.46**	0.22**	-0.10	0.14	0.14	-0.05	-0.07
	(0.11)	(0.15)	(0.18)	(0.27)	(0.19)	(0.09)	(0.07)	(0.13)	(0.12)	(0.06)	(0.05)
Liquidity *j,t*	-0.26	-0.38***	-0.25**	0.04	-0.36***	-0.48***	--	-0.30***	-0.34***	-0.14**	-0.17***
	(0.17)	(0.12)	(0.10)	(0.09)	(0.09)	(0.13)		(0.09)	(0.10)	(0.07)	(0.06)
Realized vol *j,t*	-2.80	0.47	-0.87	2.08	-3.47**	--	0.20	-0.47	--	-0.78	--
	(2.12)	(0.95)	(0.76)	(3.45)	(1.65)		(0.22)	(0.44)		(0.47)	
%Δ Dealer Assets *t*	0.26	-0.80	-0.01	-0.19	1.61	1.62**	-2.96***	-0.22	0.13	--	--
	(0.79)	(0.70)	(0.61)	(0.85)	(1.21)	(0.75)	(0.64)	(0.48)	(0.05)		
CDX IG *t*	0.14	0.11	0.28**	0.27*	0.18	0.14	-0.08	0.14	0.13	--	--
	(0.20)	(0.13)	(0.11)	(0.18)	(0.18)	(0.20)	(0.10)	(0.10)	(0.10)		
VIX *t*	0.02	-0.09	-0.06	0.20	-0.01	-0.35*	0.21	0.01	-0.06	--	--
	(0.17)	(0.24)	(0.17)	(0.23)	(0.41)	(0.18)	(0.25)	(0.14)	(0.14)		
MOVE *t*	-0.15	-0.21*	-0.22*	-0.30*	-0.07	-0.25*	0.01	-0.22*	-0.24*	--	--
	(0.17)	(0.12)	(0.13)	(0.15)	(0.17)	(0.14)	(0.08)	(0.12)	(0.12)		
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.24	0.50	0.48	0.50	0.54	0.60	0.34	0.39	0.44	0.50	0.52
Obs	41	41	36	36	36	36	41	190	226	185	220

Notes: The table shows regression results of indices of changes in maximum amounts from the SCOOS on various explanatory variables, using an alternative set of regressors to the baseline model reported in the text. The first set of columns show separate regressions for each asset class, while the second set of columns. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "six asset classes" columns exclude data on private RMBS, while the "five asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

D. Dependent variable: maximum maturities

	By Asset Class (*j*)							Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Priv. RMBS**	**Equities**	**5 asset classes**	**6 asset classes**	**5 asset classes**	**6 asset classes**
Demand *j,t*	-0.10 (0.08)	0.08 (0.16)	0.23 (0.18)	0.58*** (0.19)	0.34** (0.16)	0.11 (0.11)	-0.15* (0.08)	0.13 (0.12)	0.12 (0.11)	-0.01 (0.07)	-0.04 (0.06)
Liquidity *j,t*	-0.46*** (0.13)	-0.52*** (0.14)	-0.36** (0.14)	-0.00 (0.07)	-0.42*** (0.09)	-0.43*** (0.12)	--	-0.38*** (0.08)	-0.39*** (0.08)	-0.21*** (0.06)	-0.21*** (0.05)
Realized vol *j,t*	-2.00 (1.56)	1.13 (1.26)	0.07 (1.03)	2.03 (2.75)	-1.17 (1.44)	--	0.23 (0.16)	0.29 (0.52)	--	-0.03 (0.35)	--
%Δ Dealer Assets *t*	0.08 (0.78)	0.54 (0.79)	-0.13 (0.66)	-0.26 (1.06)	1.77* (0.98)	1.41* (0.77)	-1.41** (0.64)	0.05 (0.53)	0.27 (0.51)	--	--
CDX IG *t*	-0.04 (0.12)	0.13 (0.11)	0.09 (0.14)	0.20 (0.12)	0.11 (0.16)	-0.02 (0.13)	-0.03 (0.09)	0.07 (0.09)	0.06 (0.09)	--	--
VIX *t*	0.22 (0.22)	-0.17 (0.24)	-0.15 (0.19)	0.19 (0.23)	-0.28 (0.39)	0.16 (0.39)	0.13 (0.21)	-0.04 (0.18)	0.00 (0.22)	--	--
MOVE *t*	-0.13 (0.12)	-0.20 (0.14)	-0.15 (0.15)	-0.17 (0.17)	-0.06 (0.14)	-0.19 (0.16)	-0.06 (0.10)	-0.15 (0.11)	-0.15 (0.11)	--	--
Asset Class F.E.	--	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	--	No	No	Yes	Yes
Adj R^2	0.39	0.54	0.49	0.46	0.57	0.50	0.13	0.47	0.48	0.57	0.60
Obs	41	41	36	36	36	36	41	190	226	185	220

Notes: The table shows regression results of indices of changes in maximum maturities from the SCOOS on various explanatory variables, using an alternative set of regressors to the baseline model reported in the text. The first set of columns show separate regressions for each asset class, while the second set of columns. The first set of columns show separate regressions for each asset class, while the second set of columns shows various pooled specifications. The "6 asset classes" columns exclude data on private RMBS, while the "5 asset classes" columns exclude both private RMBS and equities. Variable construction is described in the text. Constant terms not shown. Standard errors, in parentheses, are heteroskedasticity-robust for the asset-class-level regressions and the pooled regressions with time fixed effects, and clustered by quarter for the pooled regressions with time-series controls. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

A.5 Panel regressions of funding-term indices on frequencies of stated reasons for changing terms

	Financing spreads$_{j,t}$	**Haircuts$_{j,t}$**	**Max. Amounts$_{j,t}$**	**Max. Maturities$_{j,t}$**
Counterparty risk$_t$	-0.01	0.49***	0.41*	0.77***
	(0.44)	(0.17)	(0.22)	(0.19)
Market liquidity$_t$	1.12***	0.87***	0.68***	0.46**
	(0.37)	(0.17)	(0.18)	(0.18)
Risk willingness$_t$	0.40	0.64**	0.05	0.22
	(0.50)	(0.30)	(0.27)	(0.31)
Int. treasury charges$_t$	-0.10	-0.19	0.41*	0.07
	(0.70)	(0.32)	(0.32)	(0.27)
Capital availability $_t$	0.65	0.01	-0.42	-0.23
	(0.51)	(0.22)	(0.29)	(0.24)
Competition$_t$	0.30	-0.14	0.02	0.04
	(0.34)	(0.13)	(0.15)	(0.17)
Market conventions$_t$	-0.19	-0.15	0.60**	0.21
	(0.63)	(0.24)	(0.27)	(0.26)
Asset-class fixed effects?	Yes	Yes	Yes	Yes
Adj. R^2	0.59	0.67	0.63	0.63

Notes: The table shows regressions of the SCOOS diffusion indices of the net tightening of each type of financing term, pooled across asset classes, on indices of dealers' self-reported reasons for changing terms across their institutions as a whole. Coefficients can be interpreted as the net number of dealers tightening a specific funding term for each dealer that reports tightening its institution-wide terms for a particular reason. Standard errors, using clustering by quarter, are shown in parentheses. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels. The number of observations in each regression is 267.

A.6 First-stage instrumental-variables regressions

For Liquidity

		Excluding Private RMBS		Including Private RMBS	
		Financing rate	**Max. Amounts**	**Financing rate**	**Max. Amounts**
Mkt. Conventions *t*	Hedge funds	0.57** (0.23)	0.84*** (0.15)	0.51** (0.20)	0.90*** (0.13)
	Nonfin. corps.	0.26 (0.23)	-0.13 (0.18)	0.37* (0.21)	-0.25 (0.17)
Realized vol *j,t*		0.87 (0.62)	-0.42 (0.43)	--	--
%Δ dealer equity *t*		-3.28*** (0.71)	-0.76* (0.43)	-3.83*** (0.70)	-0.65 (0.41)
CDX HY *t*		0.06** (0.03)	0.07*** (0.02)	0.06** (0.02)	0.08*** (0.02)
VIX *t*		0.45*** (0.13)	0.10 (0.10)	0.51*** (0.13)	0.01 (0.09)
10Y swaption vol *t*		-0.01 (0.15)	-0.16* (0.08)	-0.03 (0.14)	-0.15** (0.08)
T bill rate *t*		-0.23*** (0.06)	-0.14 (0.04)	-0.28*** (0.05)	-0.13*** (0.04)
Asset Class F.E.		Yes	Yes	Yes	Yes
Adj R^2					
Obs		190	190	226	226

Notes: The table shows the first-stage regressions for the two-stage least-squares estimation presented in Section 7.2 of the paper. The independent variables are the SCOOS indices of changes in financing rates and maximum amounts. Instruments are net percentages of dealers reporting tightening terms because of "market conventions" to hedge funds and nonfinancial corporations. Equities are excluded from the sample because they do not have liquidity indices, which are used in the second stage. The regressions are pooled across asset classes. Variable construction is described in the text. Constant terms not shown. Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

For Returns

		Excluding Equities		Including Equities	
		Financing rate	**Max. Amounts**	**Financing rate**	**Max. Amounts**
Mkt. Conventions *t*	Hedge funds	0.51** (0.24)	0.78*** (0.15)	0.40** (0.20)	0.77*** (0.12)
	Nonfin. corps.	0.31 (0.23)	-0.07 (0.17)	0.35* (0.20)	-0.13 (0.15)
Realized vol *j,t*		0.62 (0.65)	-0.69 (0.42)	-0.06 (1.59)	1.24 (16.43)
%Δ dealer equity *t*		-3.87*** (0.54)	-1.42*** (0.27)	-3.50*** (0.50)	-1.49*** (0.34)
GDP forecast revision *t*		-6.22*** (2.98)	-6.88*** (1.30)	-6.07*** (1.650	-6.09*** (1.30)
VIX *t*		0.61*** (0.10)	0.28*** (0.07)	0.59*** (0.10)	0.22*** (0.06)
10Y swaption vol *t*		0.01 (0.14)	-0.12 (0.09)	0.04 (0.12)	-0.10 (0.08)
T bill rate *t*		-0.12 (0.07)	-0.01 (0.04)	-0.12 (0.06)	-0.00 (0.03)
Asset Class F.E.		Yes	Yes	Yes	Yes
Adj R^2		0.59	0.66	0.58	0.62
Obs		190	190	231	231

Notes: The table shows the first-stage regressions for the two-stage least-squares estimation presented in Section 7.2 of the paper. The independent variables are the SCOOS indices of changes in financing rates and maximum amounts. Instruments are net percentages of dealers reporting tightening terms because of "market conventions" to hedge funds and nonfinancial corporations. Equities are excluded from the sample because they do not have liquidity indices, which are used in the second stage. The regressions are pooled across asset classes. Variable construction is described in the text. Constant terms not shown. Robust standard errors in parentheses. Asterisks indicate statistical significance at the 10%, 5%, and 1% confidence levels.

Table A7. Regressions of asset returns on funding terms

	By Asset Class (j)						Pooled			
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**	**Equities**	**Excl. Equities**	**Incl. Equities**	**Excl. Equities**	**Incl. Equities**
Fin. Spreads $_{j,t}$	-1.32	1.16	-4.05	-0.17	0.61	11.65*	-1.47	0.85	-3.19**	0.48
	(1.29)	(3.17)	(4.57)	(1.36)	(2.40)	(5.87)	(1.49)	(1.34)	(1.42)	(2.54)
Adj R^2	*0.45*	*0.43*	*0.75*	*0.42*	*0.41*	*0.79*	*0.40*	*0.48*	*0.70*	*0.59*
Haircuts $_{j,t}$	0.42	1.12	-2.36	3.13	5.97***	23.08	1.04	4.68**	-3.08*	3.38
	(3.55)	(6.58)	(3.59)	(2.00)	(1.94)	(16.31)	(1.75)	(2.09)	(1.64)	(3.16)
Adj R^2	*0.44*	*0.43*	*0.74*	*0.47*	*0.48*	*0.78*	*0.40*	*0.49*	*0.69*	*0.59*
Max. Amounts $_{j,t}$	-5.75**	-8.12*	-11.43*	-2.17	5.56	16.13**	-4.85**	1.91	-3.72**	5.31*
	(2.12)	(4.37)	(6.27)	(2.33)	(3.75)	(7.27)	(1.89)	(2.86)	(1.83)	(3.20)
Adj R^2	*0.56*	*0.47*	*0.78*	*0.44*	*0.45*	*0.80*	*0.42*	*0.48*	*0.70*	*0.60*
Max. Maturity $_{j,t}$	-4.97*	-1.15	-2.24	0.82	4.85	8.44	-0.95	3.30**	-2.44	3.61
	(2.48)	(4.60)	(6.86)	(2.21)	(2.85)	(6.30)	(1.61)	(1.51)	(1.63)	(3.32)
Adj R^2	*0.51*	*0.43*	*0.74*	*0.42*	*0.44*	*0.78*	*0.40*	*0.49*	*0.69*	*0.59*
Asset-class-specific controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-series controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Asset Class F.E.	--	--	--	--	--	--	Yes	Yes	Yes	Yes
Time F.E.	--	--	--	--	--	--	No	No	Yes	Yes
Obs.	41	41	36	36	36	41	190	231	190	231

Notes: The table shows regressions of quarterly asset returns on security financing terms and control variables (not reported). The first set of columns runs the regression for each asset class separately. The last two columns pool across all asset classes. Standard errors in parentheses. Asterisks indicate statistical significance at the 10%, 5%, and 1% level, using heteroskedasticity robust standard errors.

Table A.X Regressions of asset returns on funding terms, excluding Q2 2020

	By Asset Class (j)					Pooled	
	Agency MBS	**IG Corp**	**HY Corp**	**ABS**	**CMBS**		
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[7]**	**[8]**
Fin. Spreads $_{j,t}$	-0.2	0.7	-3.5	-0.9	0.6	-1.4	-3.4**
	(1.8)	(3.1)	(3.6)	(1.0)	(2.4)	(1.1)	(1.6)
Adj R^2	*0.28*	*0.35*	*0.67*	*0.28*	*0.31*	*0.38*	*0.55*
Haircuts $_{j,t}$	2.4	7.2	0.8	1.7	3.7	1.1	-3.2*
	(2.6)	(5.9)	(4.6)	(2.0)	(2.8)	(1.6)	(1.8)
Adj R^2	*0.30*	*0.38*	*0.66*	*0.28*	*0.36*	*0.38*	*0.55*
Max. Amounts $_{j,t}$	-4.4*	-2.4	-5.3	0.6	7.3**	-2.8	-4.9**
	(2.3)	(5.6)	(6.3)	(2.3)	(3.5)	(1.8)	(2.1)
Adj R^2	*0.36*	*0.35*	*0.67*	*0.26*	*0.41*	*0.38*	*0.56*
Max. Maturity $_{j,t}$	-5.0*	3.7	0.4	0.6	5.7	0.5	-2.4
	(2.5)	(4.5)	(5.6)	(1.7)	(3.5)	(1.7)	(2.0)
Adj R^2	*0.37*	*0.36*	*0.66*	*0.26*	*0.38*	*0.38*	*0.54*
Asset-class-specific controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-series controls	Yes	Yes	Yes	Yes	Yes	Yes	No
Asset Class F.E.	--	--	--	--	--	Yes	Yes
Time F.E.	--	--	--	--	--	No	Yes
Obs.	40	40	35	35	35	184	184

Notes: The table shows regressions of quarterly asset returns on security financing terms and control variables (not reported), excluding the observations from Q2 2020. The first set of columns runs the regression for each asset class separately. The last two columns pool across all asset classes. Standard errors in parentheses. Asterisks indicate statistical significance at the 10%, 5%, and 1% level.