Syndicated Debt Pricing and Equity Mispricing*

Tim de Silva†‡
Massachusetts Institute of Technology
Sloan School of Management

August 30th, 2019
Preliminary Draft

Comments welcome. Please do not circulate without permission.

Abstract

This paper studies whether a firm's current equity valuation affects the terms at which it can borrow in the primary syndicated debt market. First, I model syndicate loan terms as a function of operating performance and credit quality. Next, I provide evidence that borrowers with underpriced equity are more likely to receive abnormally high interest, small, and short loans relative to my model's predictions, suggesting mispricing in the equity market "spills over" into the primary syndicated debt market. Finally, I show this spillover is marginally weaker for firms that provide higher quality financial reports and more forward guidance. My results suggest equity mispricing has real effects on a firm's cost of capital in the primary syndicated debt market, and the quality of the firm's information environment can mitigate these effects.

*I am grateful to Eric So and Joe Weber for their substantial guidance throughout this project, Eric Lehmann and Sara Shehata from S&P for extensive discussions regarding the LCD database, and to Alex Moehring, Andrew Sutherland, Carlos Molina, David Hughes, Gabriel Pundrich, Georg Rickmann, Harindra de Silva, Jacquelyne Gillette, Ki-Soon Choi, Luca Guis, Sam Anderson, and an anonymous analyst at Goldman Sachs for helpful discussions that improved this paper. I also thank Eric So, S&P LCD, and Suzie Noh for sharing data used in this paper. This paper was prepared with the intention of meeting the MIT Sloan Accounting Group's first-year paper requirement.

†Corresponding email: tdesilva@mit.edu.

‡Corresponding address: MIT Sloan School of Management, 100 Main Street, E62-661, Cambridge, MA.

1. Introduction

This paper investigates (1) spillover in mispricing, defined as deviations from fundamental value, from equity to primary syndicated debt markets and (2) the extent to which this spillover is affected by a firm's disclosure choices. Prior literature argues for the existence of feedback effects from secondary markets, in which securities are traded among investors without capital flowing to firms, to real outcomes, through which secondary market prices can affect a firm's investment and acquisition decisions (Boot and Thakor (1997), Dow and Gorton (1997), Edmans et al. (2012), Bond et al. (2012)). This paper searches for evidence of these feedback effects from equity to primary syndicated debt, using the equity market as the secondary market and a borrower's syndicate loan terms as the real outcome. My first set of results suggests a borrower receives abnormally unfavorable loan terms relative to other borrowers with similar fundamentals when its equity is underpriced and vice versa. These results provide evidence of spillover from equity to primary market syndicated debt - the opposite direction from which existing syndicated debt literature has focused (e.g. Bushman et al. (2010)). In a second set of tests, this paper shows this spillover is marginally weaker when a firm provides more detailed financial reports and more frequent guidance, suggesting disclosure quality and quantity affect the financing options available to firms with mispriced equity.

This paper considers two mechanisms in developing and testing the hypothesis that equity mispricing influences the extent to which a borrower's loan terms deviate from those of other borrowers with similar fundamentals. First, the lead arranger[1] may learn from the equity market when setting the loan terms. Equity and debt can be viewed as contingent claims with different payoff profiles on the same underlying asset (firm value), implying that information revealed in one market should inform price discovery in the other (Merton (1974)). Existing evidence suggests credit markets inform equity markets (Acharya and

[1]The "lead arranger" is the bank or institution that sets the initial terms for the loan in the primary market. See Section 2.1 for a detailed discussion of the primary syndicate loan market.

Johnson (2007), Batta et al. (2016)), equity markets contain information relevant for estimating default risk and credit ratings (Shumway (2001), Odders-White and Ready (2006), Campbell et al. (2008)), credit rating agencies use equity market information (S&P Global Market Intelligence (2006)), and equity and bond analysts exhibit similar timeliness in their ratings (De Franco et al. (2009)). Collectively, this evidence suggests the equity market contains information relevant for primary syndicated debt pricing. If the lead arranger uses the borrower's equity price as an aggregator of this information (Hayek (1945), Holmstrom (1979)), then mispricing in the equity market will spillover into the borrower's loan terms[2].

A second mechanism through which equity mispricing could spillover into primary syndicated debt is the use of the borrower's equity valuation as a source of bargaining power when setting the loan terms. Prior to the lead arranger determining the loan terms, the borrower and lead arranger engage in a costly information-sharing process. The costs incurred by both parties during this process are relationship-specific, which implies the party with greater bargaining power may be able to adjust the loan terms to extract rents from (i.e. "hold-up") the other party (Williamson (1979)). If the borrower's equity valuation influences this bargaining power, which is likely because it represents the attractiveness of the borrower's outside financing options, then any mispricing in the equity market would spillover into the primary syndicated debt market through this hold-up.

The motivation for this paper's focus on spillover of equity mispricing into the primary syndicated debt market is twofold. First, prior literature and institutional details predict this spillover, which form the basis for my hypothesis development. Although the current version of this paper does not provide sufficient evidence to identify the source of this mispricing spillover, I hope to use these results as a starting point for distinguishing between potential channels in future work. Secondly, the syndicated debt market has become a primary venue through which non-investment grade borrowers raise capital (Section 2.1). Thus, mispricing

[2]This mechanism is related to Bond et al. (2012), who argue that managers are likely to learn from equity markets when making firm decisions due to the information aggregation role of prices.

spillover from the equity market into this market would likely have economically meaningful effects on the costs of capital for non-investment grade borrowers, in aggregate.

The latter half of this paper examines the role of disclosure choices in mitigating this mispricing spillover. Better quality accounting information increases the bankruptcy forecasting power of accounting-based measures of performance relative to market-based measures (Franzen et al. (2006), Beaver et al. (2012), Mayew et al. (2015), Givoly et al. (2017)), and mitigates contracting problems by providing a higher quality signal about firm performance (Armstrong et al. (2010), Christensen et al. (2016), Dou (2018)). More frequent voluntary disclosure improves the precision of firm value estimates (Baginski et al. (1993), Duffie and Lando (2001), Clement et al. (2003), Yu (2005)), and alleviates hold-up problems by reducing information asymmetries among lenders (Rajan (1992), Lo (2014)). These findings collectively suggest increases in disclosure quality and quantity should weaken the link between equity mispricing and abnormal loan terms, regardless of which of the two aforementioned mechanisms drives this spillover.

To identify abnormally good (and bad) loan terms, I project each borrower's terms onto a vector of firm-specific measures of operating performance and credit quality, motivated by Barth et al. (2008). This projection is done separately for three different loan terms - interest rate spread over LIBOR, loan size, and loan length - resulting in three separate residuals for each loan. I interpret these residuals as measures of the abnormality of a borrower's loan terms, because they represent differences between the loan terms given to the borrower and those given to the average company with the same publicly available measures of operating performance and credit quality. In describing my results, I refer to loan terms as "less favorable" when a borrower receives an abnormally high interest rate, small loan size, or short loan length, which corresponds to a positive spread residual, negative size residual, or negative length residual.

The first set of results in this paper suggests that a borrower receives less favorable terms in the primary syndicated debt market when its equity is underpriced and vice versa. Specifically, I find that a linear combination of the three residuals generated from the loan term projections contains strong predictive power in my sample's cross-section of equity returns - borrowers with less favorable debt terms have higher returns over the year following the loan's announcement relative to borrowers with more favorable terms. Despite this outperformance in the subsequent year, I find firms that receive less favorable terms *underperform* those that receive more favorable terms in the year *prior to* the loan's announcement (i.e. there is a return reversal).

Further tests show borrowers with less (more) favorable terms have lower (higher) market-to-book ratios prior to the loan's announcement that increase more (less) over the following year, and are classified as more undervalued (overvalued) using a composite valuation signal motivated by Piotroski and So (2012). Collectively, these results suggest mispricing in the equity market, identified via predictable patterns in returns and valuation signals, can have real effects on a borrower's ability to raise capital in the primary syndicated debt market. A significant limitation of these findings is I cannot refute that these return patterns are driven by abnormal loan terms informing equity price discovery (i.e. reverse causality) or by an omitted variable affecting both outcomes simultaneously. Since variation in equity mispricing is likely not exogenous to syndicate debt terms, I plan to address this limitation in future work by using mutual fund flows as an instrument for equity mispricing (Coval and Stafford (2007), Edmans et al. (2012)).

This paper's second set of results suggests improved financial reporting quality and increased voluntary disclosure weaken the link between a borrower's equity valuation and deviations from its expected cost of capital in the syndicated debt market. Using disaggregation quality (DQ) and the number of management forecasts as proxies for the quality of a firm's financial disclosures[3] (Chen et al. (2015)) and voluntary disclosure frequency,

[3]This measure is based on the assumption that finer information is more accurate. I discuss the suitability of this assumption for my research question in Section 5.2.

I find the link between equity mispricing and the loan term residuals marginally weakens as DQ and the number of management forecasts increase. The implications of this result depend on the mechanism through which the mispricing spillover occurs. In the context of cross-market learning (the first mechanism), this suggests improved accounting quality and increased disclosure frequency reduce the informativeness of a borrower's equity valuation relative to the lead arranger's other information sources, consistent with Beaver et al. (2012). In the context of an incomplete contracting problem (the second mechanism), this result suggests higher quality financial reports and more frequent guidance mitigate the use of the borrower's mispriced equity by one party to "hold up" the other, consistent with Lo (2014) and Dou (2018). In future work, I hope to provide stronger evidence using a measure of accounting quality that is more relevant to my research question, such as debt contracting value (Ball et al. (2008)).

This current version of this paper hopes to make three contributions. First, this paper hopes to contribute to a growing literature on the real effects of equity mispricing, which argues financial markets are more than just a "sideshow" (Morck et al. (1990), Baker et al. (2003), Chen et al. (2007), Edmans et al. (2012)). In particular, I provide preliminary evidence that deviations from fundamental value in the equity market can affect a firm's cost of capital in the syndicated debt market. Secondly, this paper hopes to contribute to the literature on the link between price discovery in syndicated debt and equity markets (Bushman et al. (2010), Ivashina and Sun (2011), Massoud et al. (2011), Addoum and Murfin (2019)). My results suggest syndicate loan terms are influenced by equity market prices, while prior literature has focused on demonstrating spillover in the opposite direction. Finally, this paper hopes to contribute to existing evidence on the role of disclosure in mitigating hold-ups (Armstrong et al. (2010), Lo (2014), Christensen et al. (2016), Dou (2018)). Conditional on providing further evidence to support the hold-up mechanism, my results suggest higher quality and more frequent disclosure alleviate hold-up, resulting in reduced financing constraints for firms with underpriced equity.

This paper is organized as follows. Section 2 discusses institutional details of the primary syndicate loan market, existing literature, and my hypothesis development. Section 3 describes my data sources and sample selection. Section 4 describes my research design, and results are presented in Section 5. Section 6 concludes with a discussion of my plans for future work.

2. Background

2.1. Overview of the Primary Syndicate Loan Market

A syndicated loan is commercial credit line provided by a group of lenders that is structured, arranged, and administered by one (or more) commercial or investment banks[4], which is often used by the borrower for refinancing, or to fund an acquisition/project. These banks are known as the arrangers and most deals have one "lead arranger". As an arranger, these banks are responsible for raising capital (*syndicating*) from other institutions (other banks or institutional investors), for which the issuer pays them a fee. These arrangers can also profit by investing in the deal themselves, but these fees are their primary source of revenue. Importantly, this fee is increasing in the complexity and riskiness of the deal. Often times high-quality investment grade companies pay little to no fee and syndicate the loans themselves, using the arrangers only for administrative purposes. Consequently, (1) the most profitable loans for arrangers are those made to borrowers with lower credit quality, which also (2) tend to be in high demand from institutional investors due to their higher spreads. These two facts motivate this paper's focus on the leveraged (non-investment grade) loan market.

In what follows I outline an example of a syndicate loan origination from start to finish. Consider **XYZ Corp**, who is looking to raise capital to finance an acquisition and wishes to use syndicated debt. **XYZ Corp** will solicit bids from different banks, such as **Bank A** and

[4] This section is based heavily on S&P Global Market Intelligence (2018), which I am grateful to S&P LCD for sharing.

Bank B, that wish to be arrangers. **Bank A** and **Bank B** will outline their strategy for syndication, their qualifications, and pricing strategy. Once **XYZ Corp** chooses an arranger (i.e. awards the "mandate"), say **Bank A**, the syndication process begins. The first step in the syndication process is for **Bank A** to prepare a report (information memorandum/"IM") describing the terms of the transaction, which usually contains an executive summary, investment considerations, a list of terms and conditions, an industry overview, and a financial model. Critically, this IM is *confidential* because while preparing it, **XYZ Corp** provides **Bank A** with non-public information, such as management forecasts/projections, pro-forma financial statements, and management's future acquisition (or disposition) plans[5]. **Bank A** will also (probably) prepare a "public" version of the IM, which will be shown to investors that wish to stay on the public side of the wall and retain their ability to trade **XYZ Corp**'s public securities. While preparing this book, **Bank A** will contact potential investors to gauge their interest and the terms at which they are willing to invest.

After preparing the IM and gauging investor interest, **Bank A** (the lead arranger) will "launch" the loan with terms that it believes will be attractive to investors. The loan terms[6] that I focus on in this paper are the loan spread (interest rate in basis points over LIBOR[7]), the loan size, and the loan term (length). These terms at which the loans are launched are called the "initial talk" terms. Most syndicate loans have multiple "tranches", so **Bank A** will propose terms for each of these tranches. There are two broad types of tranches: pro-rata and institutional. Pro-rata tranches are revolving credit lines (RC) and term loans (TLA) that are (usually) only offered to banks. Institutional tranches are term loans (TLB, TLC,

[5] According to an anonymous analyst at Goldman Sachs, all of this information gets stored in a "data room". Access is limited in this room to people who are already part of the deal or are interested in it. There appears to be substantial discretion in who is allowed access to the information in this room, which is consistent with some investors exploiting the information before it is public (Massoud et al. (2011), Ivashina and Sun (2011)).

[6] There are three other aspects of the loan that I ignore - LIBOR floor, original-issue discounts, and covenants. The three reasons for ignoring these characteristics are (1) data limitations, (2) lack of cross-sectional variation - many loans don't have a LIBOR floor or OID, and (3) the relatively small economic importance of floors and discounts.

[7] Other reference rates, like SOFR or FFR, can be used. A big current issue for syndicate loan investors is how to deal with the LIBOR phase-out.

TLD) or second-lien loans (SL) offered to institutional investors, like CLOs, mutual funds, or hedge funds. The collection of pro-rata and institutional tranches is called a "deal", while each tranche itself is called a "facility".

Following the launch of the loan, the "market flex" process begins. During this process, **Bank A** will get commitments from investors for a given price and amount of each loan facility. **Bank A** will then total up the commitments and decide where to "price" the loan, attempting to ensure there is enough interest so the loan can be made, but also that enough investors get a piece of the loan. The set of banks and institutional investors that have access to a syndicate loan in the primary market is very small - **Bank A** will likely call the clients with which it has the best relationships[8]. In deciding where to price the loan, **Bank A** will make adjustments to the loan spread and size[9] if needed, which are called "flexes". Not all loans have flexes - less than 30% of the loans flex in my sample. Once the **Bank A** decides on the terms and all flexes occur, the loan will "close". Importantly, it is possible for the loan to be "cancelled" during or after the flexing process, in which case the deal ends and **XYZ Corp** does not raise capital. The three primary reasons for loan cancellations are (1) **XYZ Corp** does not find the loan terms attractive, in which case **XYZ Corp** pays a cancellation fee to **Bank A**, (2) **Bank A** cannot stimulate enough investor interest in the loan, and (3) the acquisition or project underlying **XYZ Corp**'s need for financing falls through.

The analysis in this paper uses only the initial talk terms (i.e. loan terms at the time of launch). The reason for this is twofold. First, in some cases the difference between the dates on which the flex occurs versus when these flex terms become public is unknown. This is especially problematic in this paper because I rely on return prediction tests to identify equity mispricing. If I use information that was not available to the market at the time,

[8]According to an anonymous analyst on the Goldman Sachs syndicated debt desk, the primary factor that determines which investors get access to these deals in the primary market is the quality and profitability of an investor's existing relationships with the bank. Goldman has a list of clients which they call, and Goldman's relationship with the client determines who they call first. The fact that few investors are on this list provides a substantial limit to arbitrage for an investor who wants to correct mispricing in this market.

[9]The lead arranger (e.g. **Bank A**) can also flex the LIBOR floor and OID, however this is substantially less common.

then interpreting return prediction as mispricing is invalid - the return prediction could just be driven by look-ahead bias (Section 3). Secondly, focusing on the initial talk terms substantially reduces the potential set of channels through which mispricing spillover could occur. Since the lead arranger sets these terms, any mispricing spillover in my analysis must be driven by their incentives or behavior.

In the example of a syndicate loan deal described above, there are two frictions that are central to my hypothesis development in Section 2.4. First, by the time initial talk terms are proposed (i.e. the loan is launched), substantial deal-specific investments have been made by both the lead arranger (**Bank A**) and the issuer (**XYZ Corp**). The lead arranger has gone through the time-consuming process of preparing the IM, incurring information collection and processing costs that are the basis for the compensation of entire desks of syndicated deal desk employees. The issuer has incurred costs associated with sharing proprietary information with the lead arranger (Verrecchia (1983), Verrecchia and Weber (2006), Berger and Hann (2007)), but also has awarded the lead arranger the mandate. Awarding the mandate requires a substantial investment by the issuer, who has to review the proposals of all potential arrangers and choose the best one. Secondly, cancelling a deal after it has been launched requires the issuer to restart the entire deal process. Given the majority of syndicate loans are used to fund projects, acquisitions, or refinancing[10], it's likely that most issuers will be averse to cancelling loans on the basis of moderately unfavorable loan terms. Those who do are probably more likely to have lower NPV opportunities or less urgent financing needs.

I conclude this subsection with a brief discussion of the recent growth and trends[11] in the syndicated debt market which are important for understanding prior literature discussed in Section 2.2. First, the popularity among both borrowers and lenders has increased substantially in the past decade - the size of the leveraged loan primary market has more than

[10]Figure 1. See Section 3 for discussion.

[11]The statistics presented in this section come from S&P LCD's US Loan Interactive Volume Report on https://www.lcdcomps.com/.

tripled since 2000. In addition to the upward trend in volume, there has been a large in increase in the amount of syndicate loans held by institutional investors - the percentage of institutional ownership in leveraged loans has increased from less than 25% in 2000 to over 70% in 2017[12]. Finally, the leveraged loan market is now larger than the high-yield bond market, indicating that it has become an important instrument used by investors to gain exposure to non-investment grade debt and by low credit quality borrowers to access capital.

2.2. Information Transmission from the Syndicated Debt Market to Equity Market

The confidential information transferred between the issuer and lead arranger in a syndicate loan reduces adverse selection and moral hazard problems that arise because of information asymmetry between these two parties (Diamond (1984), Fama (1985)). Given that all members of the loan syndicate get access to this information and there are an increasing number of institutional investors within the syndicate (Section 2.1), there is significant potential for conflicts of interest between syndicate members and the issuer. Unlike banks, many institutional investors (e.g. hedge funds) are primarily concerned with maximizing the efficiency of their investment frontier. Access to this confidential information gives these institutional investors the opportunity to exploit it via trading the issuer's public securities with an informational advantage.

The extent to which institutional investors exploit this information to earn abnormal equity returns has been the subject of substantial regulatory concern and academic research. Massoud et al. (2011) perform event studies surrounding syndicate loan originations (and repricings) and find that the market reaction is significantly negative for syndicate loans in which hedge funds are involved, despite being significantly *positive* for bank-only loans. Around these announcement dates, they also find evidence of increased short-selling behavior in the issuer's stock that is only present for loans with hedge funds as lenders, which

[12] Aside from the greater flexibility of syndicated debt compared to corporate bonds, one other factor that has likely increased interest in this market since the financial crisis is the "search for yield", as discussed in Calomiris et al. (2019).

earns abnormal returns because of the negative market reaction. Ivashina and Sun (2011) look at actual holdings of institutions involved in syndicate loans and stocks surrounding loan repricings announcements. As further evidence that some syndicate members exploit their informational advantage, they find that institutional managers with loan holdings outperform other managers on their *equity* trades following the loan repricings, and that this outperformance is concentrated in the equity of the loan issuers.

The evidence from Massoud et al. (2011) and Ivashina and Sun (2011) suggests that institutional investors in syndicate loans can exploit their access to confidential information to generate abnormal returns, which implies that this information is value-relevant. To proxy for this private value-relevant information, Bushman et al. (2010) use characteristics of the loans, such as covenants, borrower credit risk, and the presence of relationship lending, and show these characteristics are associated with faster price discovery in the equity market but only for loans with institutional investors. Building on this evidence, Addoum and Murfin (2019) form zero-cost portfolios based on secondary loan market performance and show these portfolios generate significant abnormal returns.

Collectively, this literature demonstrates that the secondary syndicate loan market can lead the equity market in circumstances when there is sufficient private information being transmitted within the syndicate. There are two elements of this paper that distinguish it from the literature discussed in this section. First, it provides evidence that mispricing in the equity market can spillover into the primary syndicate debt market and affect a borrower's cost of capital, which is the opposite direction of spillover from which existing literature has focused. Secondly, this paper focuses on the relationship between price discovery in the primary loan market and the equity market. The primary market is different from the secondary market in an aspect central to my hypothesis development - terms (i.e. prices) are set through a bargaining process between the lead arranger and issuer.

2.3. Disclosure Decisions and the "Incompleteness" of Contracts

Theories of incomplete contracting are based on the assumption that contracts are inherently incomplete because the contracting parties cannot anticipate or explicitly describe all future states of the world. Inefficiencies can arise if a non-contractible event occurs that gives one party in a bilateral contract bargaining power over the other, known as "hold-ups" (Williamson (1979)). Aghion and Bolton (1992)[13] propose a solution to this problem, in which the optimal financial contract involves reallocation of control rights based on a contractible signal that serves as a noisy measure of the non-contractible state. In the context of debt contracting, measures of accounting performance (e.g. interest coverage covenants) are natural candidates for this signal (Armstrong et al. (2010), Christensen et al. (2016)), and the more accurately these measures (the signal) captures performance (the state), the lesser "the degree of incompleteness" (Aghion and Bolton (1992), p. 477).

Consistent with this prediction, Dou (2018) finds that greater debt contracting value (the strength of accounting information in predicting future credit rating changes) is correlated with a lower probability of renegotiation, which he interprets as evidence that higher accounting quality reduces the incompleteness of contracts. In the context of syndicated debt, Ball et al. (2008) show that when a borrower has a higher debt contracting value, the lead arranger keeps a smaller percentage of the loan. Since the equilibrium proportion kept by the lead arranger is the solution to a trade-off problem that balances increased adverse selection concerns that arise from the lead arranger retaining less of the loan and the lead arranger's desire to hold less of the loan for diversification, Ball et al. (2008) argue that their results are evidence of financial reporting quality reducing information asymmetry within the syndicate.

Empirical evidence also suggests an increase in the *quantity* of disclosures mitigates incomplete contracting problems. Specifically, Lo (2014) finds when lenders are exposed to

[13] Many other papers address this problem in a similar way, such as Townsend (1979), Holmstrom and Tirole (1997), Hart and Moore (1994), and Hart and Moore (1998).

funding shocks that are likely to inhibit their ability to lend, firms that borrow from these lenders increase the frequency of voluntary disclosure in the form of management forecasts. Lo (2014) argues this increased disclosure is driven by a firm's desire to reduce the information asymmetry between a firm's current lender and potential future lenders, thereby reducing the potential for "hold-up" (Rajan (1992)) when the firm switches lenders in the future.

2.4. Development of Hypotheses

In this subsection, I develop three hypotheses based on the aforementioned institutional details and literature. The first goal of this paper is to document spillover of equity mispricing into syndicated debt loan terms, which amounts to testing Hypothesis 1. The second goal is to examine the link between the strength of this spillover and disclosure choices, which amounts to testing Hypothesis 2 and Hypothesis 3. As discussed below, both mechanisms used to develop Hypothesis 1 also predict Hypothesis 2 and Hypothesis 3.

The theoretical starting point for this paper is the assumption that mispricing, defined as deviations from fundamental value[14], can exist in the equilibrium of the equity market, driven by the existence of non-fundamental demand and arbitrage limits (Grossman and Stiglitz (1980), Shiller (1984))[15]. The first mechanism through which this equity mispricing could spillover into the primary syndicated debt market is the lead arranger's use of information from the equity market to set the loan terms. Managers make investment and acquistion decisions based on equity prices (Morck et al. (1990), Baker et al. (2003), Chen et al. (2007), Edmans et al. (2012)) and credit rating agencies use equity market information (S&P Global Market Intelligence (2006))[16], suggesting the lead arranger is likely to use equity market

[14] I refer to the fundamental value of the stock as it's value if one could perfectly estimate the Williams (1938) dividend discount model.

[15] A plethora of evidence suggests mispricing is an equilibrium phenomenon in the equity market, through the presence of non-fundamental demand (e.g. Cutler et al. (1988), De Long et al. (1990), Rashes (2001), Kumar and Lee (2006), Coval and Stafford (2007), Gârleanu et al. (2009)) and arbitrage limits (e.g. Shleifer and Vishny (1997), Mitchell et al. (2002), Brunnermeier and Nagel (2004), Gârleanu and Pedersen (2011), Beneish et al. (2015), Ljungqvist and Qian (2016)).

[16] In related work, Murfin and Pratt (2019) show banks use the prices of other "comparables" when pricing

information as well. Equity market variables, such as past returns, valuation multiples, and adverse selection measures, also contain incremental predictive power relative to accounting ratios in models of default risk and credit ratings (Shumway (2001), Odders-White and Ready (2006), Campbell et al. (2008)), suggesting there is information valuable to the lead arranger in the equity market. If a borrower's equity is mispriced and the lead arranger uses equity market variables, then this mispricing will spillover into the borrower's loan terms, predicting Hypothesis 1[17].

A second mechanism that also predicts Hypothesis 1 is an incomplete contracting problem between the borrower and lead arranger. Christensen et al. (2016) (p. 404) state that one source of contractual incompleteness is that "the future state of nature is often complex and difficult to describe contractually". In the case of the mandate awarded to the lead arranger by the borrower (Section 2.1), it's impossible for the lead arranger to tell the borrower exactly what loan terms it will get, given the private information that will be collected in the process of preparing the IM will influence these terms. Since contracting on loan terms for each possible realization of events during this information collection process is impossible, the mandate is an incomplete contract.

This contractual incompleteness and the substantial relationship-specific investments[18] made by both parties (Section 2.1) jointly imply that there is potential for hold-up[19]. Which party "holds-up" the other depends on bargaining power, and the valuation of the borrower's equity is likely to influence this bargaining power. For example, if the borrower's equity

a deal. This further supports the use of equity market information by lead arrangers.

[17]This channel relies on the assumption that the lead arranger *cannot* identify the equity market mispricing, which can be justified with task complexity (Kahneman (1973), Cohen and Frazzini (2008)) or signal complexity (Cohen and Lou (2012). Although the evidence from intermediary-based asset pricing (Adrian et al. (2014)) suggests that it's unlikely the lead arranger doesn't recognize the mispricing, it is still unlikely that the lead arranger can *perfectly* identify mispricing, otherwise they would probably be working as an equity analyst. Murfin and Pratt (2019) provide a channel through which the effect of a small amount of unrecognized mispricing could become large.

[18]I view proprietary costs (Verrecchia (1983), Verrecchia and Weber (2006), Berger and Hann (2007)) as part of these investments, as discussed in Section 2.1.

[19]A third factor that increases the potential for hold-up is the presence of relationship lending (Rajan (1992), Bushman et al. (2017)), which reduces competition between arrangers to be awarded a mandate. The greater the presence of relationship lending, the more severe the hold-up problem will be (Boot (2000)).

is significantly undervalued, its financing options outside of the syndicate loan are poor, suggesting the lead arranger has more bargaining power[20]. The lead arranger's compensation increases as the borrower's cost of capital increases, so it can use this bargaining power to extract rents by giving the borrower less favorable loan terms. Since borrowers are likely averse to cancelling deals on the basis of moderately poor loan terms (Section 2.1), this second mechanism also predicts Hypothesis 1.

Hypothesis 1. "Mispricing Spillover": *A borrower will receive unfavorable (favorable) loan terms at the same time as its equity is underpriced (overpriced), relative to the average borrower with the same operating performance and credit quality.*

Improved financial reporting quality increases the bankruptcy forecasting power of accounting information relative to equity market information (Franzen et al. (2006), Beaver et al. (2012), Mayew et al. (2015), Givoly et al. (2017)). Section 2.3 provides evidence that better quality accounting information also mitigates incomplete contracting problems through providing a more accurate measure of the contracting state. Therefore, both mechanisms predict Hypothesis 2.

Hypothesis 2. *The magnitude of the spillover in equity mispricing into a borrower's loan terms is decreasing function of the borrower's financial reporting quality.*

Baginski et al. (1993) and Clement et al. (2003) show more frequent management forecasts reduce uncertainty around firm value, which is backed by theory developed in Duffie and Lando (2001). The evidence in Section 2.3 also suggests increased voluntary disclosure reduces the potential for hold-up (Lo (2014)). Thus, both mechanisms predict Hypothesis 3.

Hypothesis 3. *The magnitude of the spillover in equity mispricing into a borrower's loan terms is decreasing function of the borrower's voluntary disclosure frequency.*

[20]In the case of the borrower's equity being overvalued, the borrower might have more bargaining power because its outside financing options are good. It is also costly for the lead arranger to walk away from the deal after preparing the IM because it would forfeit all fees.

3. Data and Sample Selection

This paper uses data on primary syndicate loan deals from S&P's Leveraged Commentary & Data (LCD) database[21]. This database tracks leveraged loans, which are issued by borrowers with a non-investment grade credit rating or carry a spread of more than 125 basis points over LIBOR. Appendix A contains the list of information provided by LCD for each loan. LCD collects this data from a variety of sources, primarily from direct lines to banks and industry contacts[22] and updates their data in real-time. The unit of observation in LCD is a loan facility, so syndicate loan deals with multiple facilities will represent multiple observations.

From the information provided by LCD (Appendix A), I calculate three variables of interest: $SPREAD\_TALK$, $AMOUNT\_TALK$, and $TERM$. These variables represent (respectively) the loan spread, size, and length proposed by the lead arranger on the launch date[23]. Detailed definitions of these variables are provided in Appendix B. After calculating these variables, I select my sample as described in Panel A of Table 1. Starting with the entire LCD universe between January 1st 1999 and December 31st 2018[24], I delete observations corresponding to loan repricings, which include amendments to existing terms and add-ons of additional capital to existing loans. I choose to focus on originations, because the two mechanisms that predict Hypothesis 1 do not make clear predictions for loan repricings[25], and repricings represent a small portion of the sample ($\approx 15\%$). Next, I require that every observation has a non-missing ticker and non-missing values of my three variables of

[21] I thank S&P LCD (https://www.lcdcomps.com/) for providing this data and their extensive assistance.

[22] LCD also collects data from press articles and SEC filings.

[23] 29% of the loans in my sample have a flex of any type, while only 20% have a spread flex. This indicates these terms calculated on the launch date represent the terms at which most borrower's will borrow. This mitigates concerns that these "initial talk" terms are not good measures of a borrower's cost of capital because they could get adjust - they represent the final terms for most companies.

[24] LCD contains data back to the early 1990s, but the information needed to calculate my three variables of interest was not provided until 1999.

[25] The loan repricing/amendment process is substantially different from the origination process. No IM is prepared and there is less at stake for both the borrower and the lead arranger. Loan repricings usually occur following a specific event that changes the borrower's credit quality or following significant changes in market conditions, neither of which are related to the two mechanisms that predict Hypothesis 1.

interest. Approximately two-thirds of all loan originations are lost because the issuer is not a publicly traded company. Around 10% of the remaining observations are lost due to missing value for my three variables of interest. Finally, I merge the remaining 6,412 facility-level observations with COMPUSTAT (annual) and CRSP (monthly) according to the process described in Appendix C, resulting in 3,436 remaining facilities that constitute my final sample. COMPUSTAT data is lagged is 4 months relative to both LCD and CRSP data, returns are adjusted for delisting[26], and all variables created from COMPUSTAT (Appendix B) are winsorized at 1%-99% by year within my sample. The number of unique deals, firm-years, and firms in my final sample are presented in Panel B of Table 1.

Table 2 presents summary statistics on $SPREAD\_TALK$, $AMOUNT\_TALK$, and $TERM$ for my final sample of loan facilities. Table 2 shows pro-rata facilities are (on average) shorter, smaller, and carry lower spreads. Pro-rata facilities likely have lower spreads because the lender (i.e. banks) generate other sources of revenue from loan deals aside from the interest payments (e.g. fees), while institutional investors' only source of revenue is interest payments. Within the different types of pro-rata (RC, TLA) and institutional facilities (TLB, TLC, TLD, SL), there is not much variation in loan terms.

Table 3 presents summary statistics for borrowers in my final sample; Table 4 presents correlation matrices between these borrower characteristics and loan terms. Table 3 shows borrowers in my sample tend to be smaller, slightly more levered, more profitable, and more likely to pay dividends than the average COMPUSTAT firm. Less than 25% of the borrowers in my sample fall below the median COMPUSTAT (or CRSP) firm's market capitalization, indicating my sample is likely not dominated by Microcaps, a concern raised by Fama and French (2008). Panel A of Table 3 also shows the median firm in my sample experiences a return reversal surrounding it's loan launch: it outperforms the market by 3% in the year

[26] CRSP returns are adjusted for delisting, if a delisting occurs and a return exists. If a delisting return is missing and the delisting is performance-related, I impute a return of −30% (Shumway (1997), Beaver et al. (2007)). I define delistings as performance-related if the CRSP delisting code is greater than or equal to 400 and less than 600.

prior to their loan's launch and underperforms by 1% in the year following the launch[27]. These return distributions are positively skewed. Table 4 shows borrower characteristics are highly correlated with loan terms in intuitive directions: larger and more profitable firms receive bigger loans with lower spreads.

Figure 1 plots a histogram of the different financing needs of borrowers in my sample. The two most common reasons borrowers raise capital are for refinancing and acquisitions, both of which represent urgent financing needs for the borrower - debt refinancing often occurs in order to meet upcoming obligations or during bankruptcy, and acquisitions are unlikely to be delayed in order to change financing terms. In the context of the development of Hypothesis 1, this suggests that most issuers are likely to be averse to cancelling loans on the basis of moderately unfavorable loan terms.

I conclude this section with a brief discussion of why my analysis uses LCD for syndicate loan data instead of the more commonly used data source Thomson Reuters' DealScan[28]. For each loan, DealScan contains the final terms and the date on which the loan facility becomes active (the money is transferred from the borrower to the lender), but loans can be entered into the database *after* this date (i.e. back-filled). On the other hand, LCD contains the launch date, the loan terms proposed on the launch date (initial talk terms), and updates the database in real-time. These differences highlight two benefits of using LCD instead of DealScan in my analysis. First, DealScan introduces look-ahead bias in return prediction tests (Section 5.1) because of back-filling. Secondly, LCD provides the initial talk terms and the launch date, which corresponds to the date at which the initial talk terms become public information. Having a set of loan terms and the date these terms became public (in contrast to DealScan, where there is no way to know when the provided terms became public) allows me to more accurately identify return reactions and reversals, since I have precise knowledge

[27]The large outperformance in the pre-period is due to the majority of the firms in my sample having a market beta above 1.

[28]The overlap between LCD and DealScan is around 30-50%, depending on the matching criteria used (Bruche et al. (2017)).

of when the market gained access to this information[29].

4. Identifying Abnormal Loan Terms

The goal of these section is to develop measures of the abnormality of a borrower's loan terms, which are used to test my three hypothesis in Section 5. These measures are signed to distinguish between abnormally *un*favorable and favorable terms, cardinal, and could have been estimated using a market participant's information set at any point in time (i.e. no look-ahead bias). The intuition underlying the methodology described below is as follows: I model loan terms as a function of the borrower's characteristics and classify loan terms as "abnormal" if they deviate from my model's prediction.

The first step in my methodology is to estimate Equations (1), (2), and (3) with OLS[30], for each loan facility I in my sample $\mathcal{S}$, where i indexes a loan facility that launched prior to loan I, b indexes the corresponding borrower, and X_b is a vector of borrower characteristics. PR_i, $INST\_TL_i$, and SL_i are indicator variables equal to one if facility i is pro-rata (RC, TLA), an institutional term loan (TLB, TLC, TLD), and second-lien (SL), respectively. Importantly, Equations (1), (2), and (3) are estimated separately for each loan facility in my sample ($I \in \mathcal{S}$) *using only the loans that launched prior to that facility*, avoiding look-ahead bias. Each separate estimation for loan facility I provides $\left\{\hat{\varepsilon}_i^s, \hat{\varepsilon}_i^a, \hat{\varepsilon}_i^t\right\}$ for every loan facility i that launched prior to loan facility I, but I only keep the set of residuals corresponding

[29] There are two other benefits of using LCD relative to DealScan. First, LCD contains more granular information about the types of each loan facility - each loan facility is classified as institutional or pro-rata, while in DealScan loans are often classified as "Term Loans", leaving the type of institution that holds the loan ambiguous. Secondly, inferring whether a deal is an origination or repricing is often impossible in DealScan, but is straightforward in LCD. This is important, given that this paper focuses on originations.

[30] In reality, the spread, size, and term of a loan are endogenous features that are related to each other bi-directionally, and other exogenous factors, like borrower characteristics. This results in a three equation simultaneous equation model, that is only identified if further assumptions are made about the direction of relationships between the endogenous variables, and about which exogenous variables are excluded from each structural equation. Bharath et al. (2009) pursue this estimation strategy, but I do not wish to make the assumption that these three loan terms do not affect each other endogenously, because the initial talk values of these three variables are proposed simultaneously. My estimation procedure consists of estimating the reduced form of the three variable simultaneous equation model. Although I cannot identify coefficients without further assumptions, these residuals still have the desired interpretation for my research question.

to $i = I$. After repeating this procedure for every loan facility in my sample ($I \in \mathcal{S}$), I have a set of residuals $\left(\left\{\hat{\varepsilon}^s_I, \hat{\varepsilon}^a_I, \hat{\varepsilon}^t_I\right\},\ \forall I \in \mathcal{S}\right)$ that represent the differences between observed loan terms for the issuer and those given to the average borrower (among loans launched prior to i) with the same public measures of operating performance and credit quality.

$$SPREAD\_TALK_i = X_b' * \beta^s + PR_i * \delta^s + INST\_TL_i * \gamma^s + SL_i * \theta^s + \varepsilon^s_i \tag{1}$$

$$AMOUNT\_TALK_i = X_b' * \beta^a + PR_i * \delta^a + INST\_TL_i * \gamma^a + SL_i * \theta^a + \varepsilon^a_i \tag{2}$$

$$TERM_i = X_b' * \beta^t + PR_i * \delta^t + INST\_TL_i * \gamma^t + SL_i * \theta^t + \varepsilon^t_i \tag{3}$$

My choice of borrower characteristics (X_b) is presented in Equation (4). This choice is motivated by Barth et al. (2008), who estimate the relationship between credit rating and LOG_AT, D_A, ROA, I_DIV, and $SUBDBT$. $EBITDA\_REVT$ is added because S&P measures profitability using this ratio when assigning credit ratings[31]; $CAPX\_AT$ and $ACCRUALS\_AT$ are included because S&P uses these variables to estimate cash flow when assessing a companies ability to cover its interest expense (S&P Global Market Intelligence (2019)). Finally, I include S&P credit ratings (SP_CCR) because an issuer's credit rating is the most salient measure of its creditworthiness to market participants, and an indicator variable for if the borrower is not rated by S&P (NR) to avoid extending the linear relationship between credit ratings and loan terms to unrated borrowers. For reference, I present the results from estimating Equations (1), (2), and (3) *on my entire sample* in Appendix D, using the choice of X_b in Equation (4). The results are consistent with Table 4.

$$X_b = \Big(LOG\_AT \quad D\_A \quad ROA \quad EBITDA\_REVT \quad CAPX\_AT \quad ACCRUALS\_AT \quad I\_DIV \quad SUBDBT \quad SP\_CCR \quad NR\Big)' \tag{4}$$

[31] I omit the ratio of EBITDA to total debt, despite is common use in industry, because it is a meaningless measure for companies with little debt (25% of my sample).

Using $\left\{\hat{\varepsilon}_I^s, \hat{\varepsilon}_I^a, \hat{\varepsilon}_I^t\right\}$, I calculate $SPREAD\_RES$, $AMOUNT\_RES$, and $TERM\_RES$ using Equations (5), (6), and (7), where standardize$(\cdot)$ denotes the function for standardizing a variable to have zero mean and unit variance *using only residuals from loan deals launched prior to* I, avoiding look-ahead bias. My fourth measure of loan term abnormality, $COMB\_RES$, combines the previous three measures (Equation (8)). I make a sign adjustment to $SPREAD\_RES$ in Equation (8) such that high values of $COMB\_RES$ correspond to more favorable loan terms.

$$SPREAD\_RES_I = \text{standardize}\left(\hat{\varepsilon}_I^s\right) \tag{5}$$

$$AMOUNT\_RES_I = \text{standardize}\left(\hat{\varepsilon}_I^a\right) \tag{6}$$

$$TERM\_RES_I = \text{standardize}\left(\hat{\varepsilon}_I^t\right) \tag{7}$$

$$COMB\_RES_I = -SPREAD\_RES_I + AMOUNT\_RES_I + TERM\_RES_I \tag{8}$$

The final step in my methodology is to combine these residuals for deals with multiple facilities into one observation, so that my unit of observation is a loan deal. I do this by choosing the largest absolute values of $SPREAD\_RES$, $AMOUNT\_RES$, $TERM\_RES$, and $COMB\_RES$ across the multiple facilities within a given deal and using those values as the corresponding residuals for that loan deal.

Summary statistics on my final sample of loan residuals for each loan deal are presented in Appendix E. This sample of loan deals is the same as my final sample in Table 1, except loans launched prior to January 1st, 2000 are dropped to ensure sufficient observations were used in the estimation of Equations (1), (2), and (3). The loan residuals summarized in Appendix E are the loan residuals used in all tests in Section 5. Appendix E also shows that the first principal component of $SPREAD\_RES$, $AMOUNT\_RES$, and $TERM\_RES$ loads negatively on $SPREAD\_RES$, but positively on both $AMOUNT\_RES$ and $TERM\_RES$. This suggests that the sign adjustment to $SPREAD\_RES$ in Equation (8) is justified, because abnormally large, long, or high-interest loans appear to represent a similar latent construct. Moreover, $COMB\_RES$ is highly correlated with the first principal component of these three residuals, suggesting it summarizes the information contained in $SPREAD\_RES$, $AMOUNT\_RES$, and $TERM\_RES$ succinctly.

A significant limitation of this methodology as presented is that it does not allow the mapping between firm fundamentals and loan terms to be time-varying. This concern could be addressed by introducing year of launch date fixed effects or by estimating the regression in rolling windows. I choose not to do either, because my small sample does not have sufficient within year variation[32].

5. Empirical Results

5.1. Mispricing Spillover: Hypothesis 1

Table 5 presents my first test of Hypothesis 1, which is the main result of this paper. This test is motivated by Coval and Stafford (2007), who argue

> "Fundamental value is not immediately observable, but by studying systematic patterns in abnormal returns over time, we can *identify deviations between transaction prices and fundamental values* ex-post if we find evidence of significant price reversals." (p. 481, *emphasis added*)[33]

To identify predictable return reversals, I estimate Fama and MacBeth (1973) (Fama-MacBeth) regressions of the borrower's equity returns on the loan residuals from Section 4 in "event-time", where I define the "event" as the loan launch that takes place at $t = 0$. I control for other factors that determine the cross-section of expected returns: book-to-market and size (Fama and French (1992)), gross-profitability (Novy-Marx (2013)), and long-run and short-run momentum (Jegadeesh and Titman (1993)). Panel A presents the results from

[32] My results are not robust to using rolling windows (e.g. one or two years), because residuals are estimated too imprecisely.

[33] Formally, this argument works as follows. The efficient market hypothesis says that $P_t = V_t,\ \forall t$, where P is the market price and V is fundamental value (Lee and So (2015)). A corollary of this is that returns follow a "random walk" (i.e. are not predictable). The contrapostive of this corollary states that if returns are predictable, then $P_t \neq V_t,\ \forall t$. This paper relies on this contrapositive to identify mispricing.

estimating Fama-MacBeth regressions over the year following the loan launch, which corresponds to estimating twelve cross-sectional regressions - one for each $t \in \{1, ..., 12\}$, where t is measured in event-time. Panel B presents results from Fama-MacBeth regressions over the year prior to the loan launch ($t \in \{-12, ..., -1\}$).

The results in Panel A of Table 5 show a borrower's expected return in the year following the loan launch *increases* as its loan terms become more unfavorable. The loan term residuals, except $AMOUNT\_RES$, significantly explain my sample's cross-section of equity returns in event-time: $SPREAD\_RES$ is positively associated with future returns, and $TERM\_RES$ and $COMB\_RES$ are negatively associated with future returns[34]. The coefficient in column (7) indicates that a one standard deviation increase in the unfavorability of a borrower's loan terms (decrease in $COMB\_RES$) increases cumulative abnormal expected returns by 4.1% over the following year. Panel B shows a borrower's expected return in the year prior to the loan launch *decreases* as its loan terms become more unfavorable: $SPREAD\_RES$ is negatively associated with past returns, and $TERM\_RES$ and $COMB\_RES$ are positively associated with past returns[35].

Collectively, the evidence in Table 5 demonstrates an association between the abnormality of a borrower's loan terms and a return reversal - borrowers with less favorable loan terms underperform those with more favorable terms prior to the loan launch but outperform

[34] The t-statistics in Table 5 Panel A are below the cutoff of 3 suggested by Harvey et al. (2016) to avoid "data-snooping". Although this suggests my results should be interpreted with caution, (in my understanding) their concerns are with large sample asset pricing tests. This paper performs asset pricing tests using a very small sample relative to asset pricing papers that attempt to estimate the SDF for the entire cross-section of expected returns, so my results are probably less subject to their concerns. However, my results are subject to generalizability concerns because of the small sample, which I discuss in Section 6.

[35] Some of the coefficients in Panel B on covariates measured from CRSP and COMPUSTAT differ in signs from Panel A (and prior literature), specifically the coefficients on gross profit and long-run momentum. This could be because these Fama-MacBeth regressions are run in event-time among a sample of companies that will be receiving loans, so to the extent that there is selection into who recieves loans, these coefficients have may not have their usual signs. For example, suppose loans are generally given to more profitable borrowers, where profitability is measured with a lag. Borrowers with low measured profitability may only get loans if recent news suggests their profitability will improve, which would result in an increased stock price in the pre-period. In this example, estimating Fama-MacBeth regressions only among borrowers that receive loans would result in low profitability borrowers outperforming high profitability borrowers in the pre-period, due to selection. I fully acknowledge that this is an ex-post rationalization and am open to suggestions on what could be driving these unusual coefficients in Panel B.

following the launch. The results in Panel B alone do not provide evidence mispricing - lenders could simply be reacting to new information that has been incorporated into equity prices but is not reflected in past fundamentals. However, Panel A shows *future* abnormal returns also are associated with loan terms. Following the argument from Coval and Stafford (2007), the predictable price reversal shown in Panels A and B (and plotted in Figure 2) suggests the equity of borrowers with less favorable loan terms is underpriced relative to that of borrowers with more favorable loan terms at the time of the loan launch, supporting Hypothesis 1.

Table 6 presents my second test of Hypothesis 1, where I regress each loan term residual onto four different measures of equity mispricing. The first measure is the market-excess return reversal from the year prior to the year following the loan launch ($\text{ExReturn}_{1,12} - \text{ExReturn}_{-12,-1}$), which is motivated by the results from Table 5. The second and third measures are book-to-market prior to the loan launch (BTM_{-1}), and the magnitude of the book-to-market reversal over the year following the loan launch ($BTM_{12} - BTM_{-1}$). Book-to-market is often used as a measure of cheapness in equity valuation (Grahman and Dodd (1934)), so Hypothesis 1 predicts the book-to-market ratio should be relatively high for borrower's with unfavorable loan terms at the time of the loan launch, and should increase (decrease) less (more) in the future as mispricing corrects. Lastly, I calculate a composite valuation signal for the borrower's equity in the month prior to the loan launch (VAL_{-1}), which captures both cheapness and quality, motivated by Piotroski and So (2012). The calculation of VAL is detailed in Appendix B, but intuitively it represents the difference between a stock's market-to-book ratio and its Piotroski (2000) FSCORE. Stocks with low market-to-book ratios and high FSCOREs (low VAL) are likely to be undervalued (Piotroski and So (2012)), so Hypothesis 1 predicts VAL_{-1} should be lower for borrowers with more unfavorable loan terms.

The results in Table 6 are consistent with Hypothesis 1: larger return reversals, higher book-to-market ratios, smaller book-to-market reversals, and lower VAL are associated with more unfavorable loan terms (Panel D), all of which suggest borrowers with more undervalued equity receive abnormally unfavorable loan terms[36]. Panels A, B, and C suggest equity mispricing spills over into the loan spread and loan length but not into the loan size. This is consistent with "initial talk" amounts primarily being determined by the borrower's needs, such as the amount of debt to refinance or the size of acquisition/project (S&P Global Market Intelligence (2018)).

The results in Tables 5 and 6 and Figure 2 collectively imply mispricing in the equity market can have real effects on a borrower's ability to raise capital in the primary syndicated debt market, which is this paper's main result. On the other hand, these results do not provide evidence to distinguish between cross-market learning or the hold-up problem (Section 2.4) as sources of this mispricing spillover. I provide preliminary tests to distinguish between these two mechanisms in Section 5.4, but hope to pursue more rigorous tests in future work.

These findings are also subject to a significant limitation: variation in all four of my proxies for equity pricing are likely not exogenous to the loan residuals. Thus, my findings cannot rule out concerns about reverse causality or a correlated omitted variable. My results are likely more robust to concerns about reverse causality, because I find evidence of equity mispricing using book-to-market and VAL, which are measured prior to the loan launch. However, I provide no evidence against the possibility that an omitted variable affects equity mispricing and loan terms simultaneously. I hope to address this limitation in future work by using a source of variation in equity mispricing that is more likely to be exogenous, such as mutual fund flows (Edmans et al. (2012)).

[36] These results are robust to including an indicator variable for if a loan was launched between 2007-2009, during the financial crisis. Including this indicator variable in level and interacting it with my explanatory variables results in a smaller main effect by around 30%, but statistical significance is unchanged.

5.2. Financial Reporting Quality and Mispricing Spillover: Hypothesis 2

Hypothesis 2 predicts the mispricing spillover documented in Section 5.1 should weaken as a borrower's financial reporting quality increases. To measure financial reporting quality, I use disaggregation quality (DQ) from Chen et al. (2015), which captures the level of disaggregation of a firm's accounting data by counting non-missing COMPUSTAT line items. A higher value of DQ is associated with better financial reporting quality, under the assumption that finer information is more accurate (Blackwell (1951)). My tests use DQ_DEMEAN_{-1}, which is DQ measured prior to the loan launch, de-meaned using the yearly average across all firms in COMPUSTAT (Appendix B)[37].

Table 7 presents my test of Hypothesis 2, in which I estimate the same cross-sectional regressions in Table 6, but include DQ_DEMEAN in level and interact it with my four measures of equity mispricing[38]. The results are weakly supportive of Hypothesis 2 when return reversals ($\text{ExReturn}_{1,12} - \text{ExReturn}_{-12,-1}$) are used as a measure of equity mispricing: the association between return reversals and the loan residuals weakens as a borrower's financial reporting quality increases. Specifically, a one standard deviation increase DQ_DEMEAN reduces the association of equity mispricing ($\text{ExReturn}_{1,12} - \text{ExReturn}_{-12,-1}$) with $SPREAD\_RES$ by 38% and with $TERM\_RES$ by 54%[39]. However, these economic magnitudes should be interpreted cautiously, given the relatively weak statistical significane. Table 7 also shows DQ_DEMEAN is strongly correlated with $TERM\_RES$, and weakly correlated with $SPREAD\_RES$. This is consistent with Bharath et al. (2008), who measure financial reporting quality using abnormal accruals and find borrowers with poor accounting quality receive shorter loans.

The results in Table 7 are weakly supportive of Hypothesis 1, implying that higher

[37] I demean by year since all of my tests are in event-time. This ensures my tests only use cross-sectional variation in financial reporting quality.

[38] The results using $COMB\_RES$ are omitted for brevity, but are identical in interpreation to Panels A and C.

[39] The standard deviation of DQ_DEMEAN in my sample is approximately 0.06.

financial reporting quality increases the relative informativeness of accounting information for the lead arranger and/or reduces the use of the borrower's mispriced equity by one party to "hold-up" the other, depending on which mechanism is the source of the spillover. In future work, I hope to provide stronger tests of Hypothesis 2 by using a different measure of accounting quality, such as debt contracting value (Ball et al. (2008)). As argued in Dechow et al. (2010), measures of financial reporting quality are context specific. Debt contracting value is likely a more relevant measure to use in testing Hypothesis 2 because it captures the timeliness with which accounting information predicts deteriorations in credit quality, and Hypothesis 2 is formed on the basis of greater accounting quality improving the precision of credit risk estimation[40].

5.3. Voluntary Disclosure Quantity and Mispricing Spillover: Hypothesis 3

Hypothesis 3 predicts the association between equity mispricing and a borrower's abnormal loan terms should weaken as a borrower discloses more frequently. Following Baginski et al. (1993), Clement et al. (2003), Lo (2014), and Noh et al. (2019), I measure voluntary disclosure frequency using management forecasts from I/B/E/S[41]. Specifically, I calculate $\Delta ln(GUIDANCE)_{-1}$, which is the change in the natural logarithm of one plus number of management forecasts issued by a firm between the quarter prior to the loan launch and the same calendar quarter one year ago (Appendix B).

My test of Hypothesis 3 is presented in Table 8. The evidence for Hypothesis 3 is slightly stronger than for Hypothesis 2: Table 8 shows more frequent management guidance leading up to the loan launch relative to one year ago weakens the association between equity mispricing and loan term residuals, specifically $SPREAD\_RES$ and $TERM\_RES$, when equity mispricing is measured using $\text{ExReturn}_{1,12} - \text{ExReturn}_{-12,-1}$ or VAL_{-1}. A one standard deviation increase in $\Delta ln(GUIDANCE)_{-1}$ reduces the association of equity mispricing

[40] The reason I didn't use debt contracting value in the current version of this paper is my sample is not large enough to estimate it. In future work, I plan to use DealScan to enlarge my sample.

[41] I thank Suzie Noh for her assistance in working with I/B/E/S data.

with $SPREAD\_RES$ by 42-57% and with $AMOUNT\_RES$ by 51-91%, depending on the measure of equity mispricing used[42]. Like the results in Section 5.2, these magnitudes should be interpreted with caution given the relatively weak statistical significance. Table 8 also shows $\Delta ln(GUIDANCE)_{-1}$ is negatively correlated with $SPREAD\_RES$. This is consistent with the evidence in Lo (2014) that more frequent management forecasts reduces information asymmetry among lenders, allowing the borrower to get better loan terms.

Collectively, Tables 7 and 8 suggest decreasing the opaqueness of a borrower's information environment, either through more frequent or higher quality disclosures, reduces the extent to which equity mispricing affects its cost of capital in the primary syndicated debt market. Comparing the results in Tables 7 and 8 suggests increasing quantity of disclosures is a more effective tool for a borrower with underpriced equity to avoid receiving unfavorable loan terms than increasing disclosure quality. I hope to explore the extent to which borrowers with underpriced equity can adjust these two dimensions of their disclosures to reduce their cost of capital in the syndicated debt in future work once I have a better understanding of the mechanism driving this mispricing spillover.

5.4. Distinguishing between Mechanisms of Hypothesis 1

This section presents two additional tests that are preliminary attempts to distinguish between the two mechanisms that predict Hypothesis 1: cross-market learning and a hold-up problem. In the first test, I look the asymmetry of the results in Table 6 - the hold-up problem predicts an asymmetric effect, while cross-market learning does not. In the context of the hold-up problem, it's more likely for the lead arranger to hold up the borrower than it is for the borrower to hold-up the lead arranger, because the borrower is dependent on the lead arranger to lend capital (i.e. the lead arranger has "residual control rights"). In ex-post renegotiation of incomplete contracts, only the party with residual control rights has the ability to hold-up (Hart (2016)) - if the other party were to attempt a hold-up, the party

[42] The standard deviation of $\Delta ln(GUIDANCE)_{-1}$ in my sample is approximately 0.6.

with the control rights would simply walk away. Therefore, the hold-up problem predicts mispricing spillover *only* when the lead arranger has an incentive to perform a hold-up, which occurs when the borrower's equity is underpriced.

Table 9 presents my test of asymmetric mispricing spillover. To test for asymmetry, I create a dummy variable ($I\_UNDERPRICED$) for each of my four measures of equity mispricing separately. $I\_UNDERPRICED$ equals one if the mispricing measure indicates the borrower's equity is underpriced relative to the median borrower in my sample, and zero otherwise. Since the four mispricing measures can have different signs, I specify in Table 9 whether $I\_UNDERPRICED$ equals one if that measure is above or below the median.

The results in Table 9 suggest the mispricing spillover is asymmetric: for three out of four measures of equity mispricing, I find the mispricing spillover in Table 6 is concentrated in cases where the borrower's equity is underpriced. These results provide preliminary evidence in favor of the hold-up problem and against cross-market learning. However, in two out of four cases, mispricing spillover occurs in the opposite direction predicted by Hypothesis 1 when the borrower's equity is overpriced. This is difficult to explain in the context of either mechanisms, suggesting further evidence is warranted.

My second preliminary test to distinguish between the two mechanisms predicting Hypothesis 1 is to examine whether the spillover in Table 6 varies by loan facility type. The hold-up mechanism is driven by the lead arranger extracting rents from the borrower (when it has bargaining power), which suggests the greater the share of the loan the lead arranger holds, the more motivated it will be to hold up the borrower. To test this implication, Table 10 presents the results from performing the same analysis in Table 6 separately by loan facility type (pro-rata and institutional term loan)[43].

The results in Table 10 suggest mispricing spillover is weaker for pro-rata loan facilities than for institutional facilities. At first glance, these results are not supportive of the hold-up

[43]Second-lien loans are excluded from the analysis because there are too few of them to generate a set of residuals among on themselves, as is described in Table 10.

mechanism. However, there are two explanations for why this finding could occur, even if the hold-up problem was the source of mispricing spillover. First, it could be that the loans with the most attractive terms are the ones the lead arranger doesn't get to keep[44]. My tests use initial talk terms, so if the lead arranger proposes very unfavorable terms for the borrower (favorable for lenders), the loan could attract more pro-rata lenders, resulting in the lead arranger holding onto less of the loan. Secondly, the lead arranger may want to give the most profitable loans (from a lender's perspective) to institutional investors because it helps generate future business. The lead arranger's biggest concern when syndicating a loan is getting enough interested investors so the deal can close (S&P Global Market Intelligence (2018)). By providing clients with profitable past deals, the lead arranger is more likely to be able to raise money in future deals through good relationships[45].

The results in this section are inconclusive in distinguishing between the two mechanisms predicting Hypothesis 1 - Table 9 is supportive of hold-up; Table 10 is not. In future work, I hope to improve the test in Table 10 by using data on the percentage of the loan actually held by the lead arranger (from DealScan) to perform this test *within* pro-rata facilities. This avoids making the implicit assumptions that the lead arranger profits more from hold-ups on pro-rata tranches than institutional tranches, and that the lead arranger holds onto a portion of all pro-rata facilities.

6. Conclusion

This paper studies whether mispricing in the equity market has real effects on a borrower's cost of capital in the primary syndicated debt market, and the extent to which the quality of a borrower's disclosure environment mitigate these effects. My primary results (Tables 5 and 6, Figure 2) suggest equity market mispricing "spills over" into syndicate loan terms. My

[44]Importantly, just because a loan has a pro-rata tranche doesn't mean the lead arranger actually keeps any of the loan.

[45]This is consistent with my discussion with an analyst from Goldman Sachs, who said that lead arrangers often rely on past relationships in determining which clients have access to future deals.

second set of results (Tables 7 and 8) provide weak evidence that a less opaque disclosure reduces this spillover. Additional tests (Tables 9 and 10) provide mixed evidence on the source of mispricing spillover.

My results are subject to a severe limitation: they rely on the assumption that variation in equity mispricing is exogenous to syndicate debt terms. In future work, I hope to relax this assumption by using mutual fund flow data (Coval and Stafford (2007)) as an instrument for equity mispricing, following Edmans et al. (2012).

Conditional on my results being robust to the use of mutual fund flow data, I also hope to pursue two additional tests to isolate the source of mispricing spillover. First, I hope to use DealScan data to test whether the degree of mispricing spillover is increasing in the percentage of the loan held by the lead arranger - the hold-up mechanism predicts it should be. Secondly, I hope to leverage S&P LCD's data on cancelled deals. Specifically, I hope to test whether cancelled deals would have had the greatest mispricing spillover, which is what the hold-up mechanism predicts.

Finally, conditional on the hold-up problem being the source of this mispricing spillover, I hope to add to existing literature on the role of disclosure in mitigating hold-ups (e.g. Lo (2014)). Specifically, I hope to demonstrate that higher quality financial disclosures can reduce hold-up, *and* consequently improve a borrower's loan terms. To do this, I plan to improve the tests in Tables 7 and 8 in two ways. First, I hope to perform larger sample tests of whether increased financial reporting quality decreases this spillover using DealScan data. This will improve the statistical power of my tests, and allow for tighter identification of abnormal loan terms using industry-year fixed effects. Secondly, I hope to use a measure of accounting quality that more accurately captures the economic constructs that support Hypothesis 2 and Hypothesis 3, such as debt-contracting value (Ball et al. (2008))[46].

[46]I thank Andrew Sutherland for helpful discussions that shaped my plans for future work.

Figure 1. Borrower Financing Needs

This figure plots the frequency of each loan purpose category, in my final sample from Table 1. These loan purpose categories are defined by S&P LCD and each loan is classified into one of these categories. For brevity, I have combined the following categories into one category labeled "Recapitalization": Recap/Dividend, Recap/Stock Repurc, Recap/Equity Infus, Recap/General Recap. The total number of observations in this table is 2,101, corresponding to the number of unique deals in my final sample from Table 1.

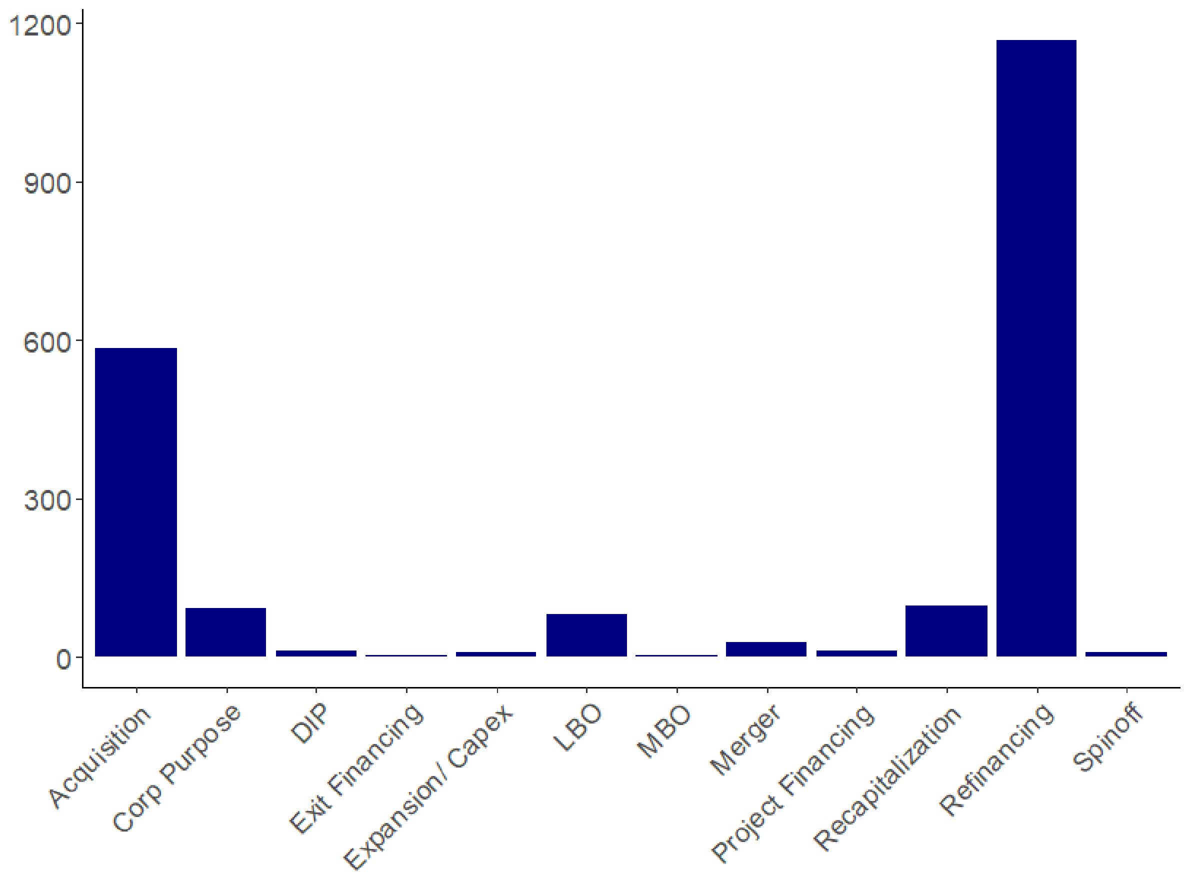

Figure 2. Return Reversal: Hypothesis 1

This figure plots the cumulative monthly return in event-time of a long-short portfolio formed at $t-12$ (12 months before loan launch). The portfolio is equal-weighted and buys the equity of borrowers with a value of $COMB\_RES$ in the bottom quintile of my sample (least favorable loan terms), and shorts the equity of borrowers with a value of $COMB\_RES$ in the top quintile of my sample (most favorable loan terms). This figure uses the same sample as Table 5. Note that this portfolio is formed with look-ahead bias because stocks are bought at $t-12$ based on information released at $t = 0$. The returns are also in event-time, so they don't represent a strategy available to an investor in real-time. The point of this figure is to graphically illustrate the return reversal documented in Tables 5 and 6.

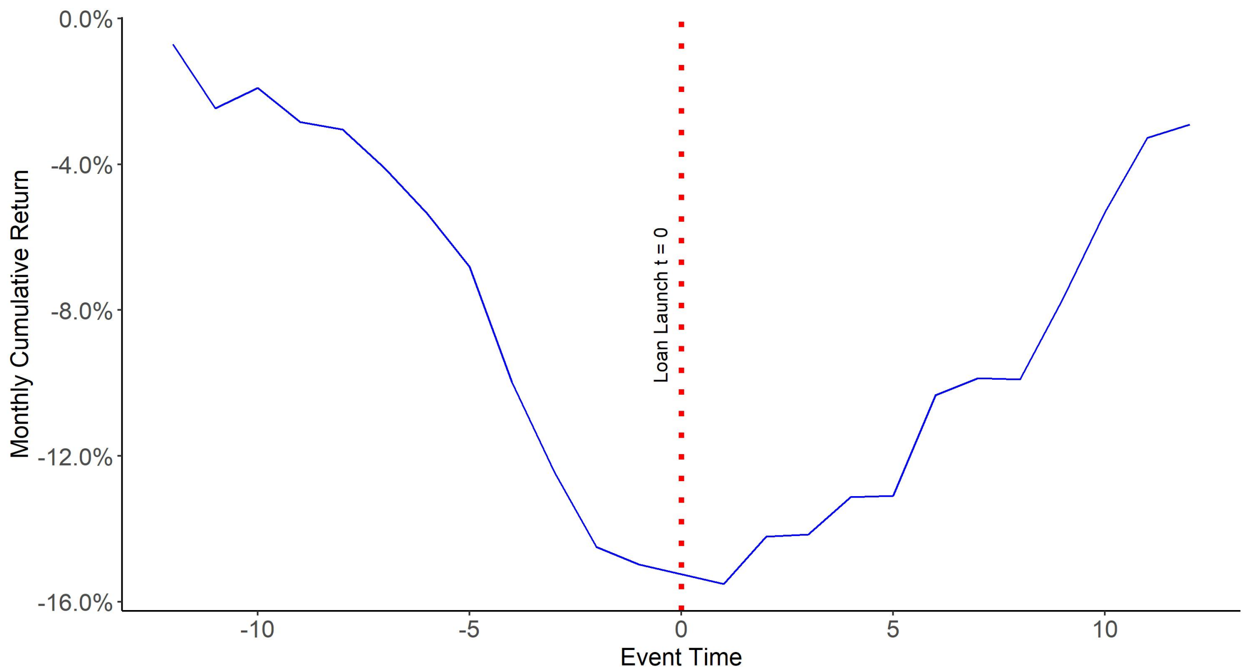

Table 1. Sample Composition

Panel A presents a breakdown of how each sample selection criteria I use reduces my sample size. The numbers presented in the right column of Panel A are the number of *facility-level* observations, based on the criteria on the left. I start with the entire LCD database, where the unit of observation is a loan facility. I then filter the sample based on facilities that correspond to deals that are originations and have non-missing tickers. Next, I require that facilities have non-missing values of $SPREAD\_TALK$, $AMOUNT\_TALK$, and $TERM$. Finally, I merge my dataset with CRSP and COMPUSTAT. The criteria I use for the merge are discussed in Section 3. Panel B shows the number of unique facilities, deals, firm-years, and firms in my final sample. For variable definitions, see Appendix B. I thank Marek Hlavac for the use of Stargazer to prepare tables in this paper (Hlavac (2018)).

Panel A: Sample Filtering	
LCD universe (January 1, 1999 to December 31, 2018)	25,574
Originations	20,668
Non-missing ticker	7,067
Non-missing values for $SPREAD\_TALK$, $AMOUNT\_TALK$, and $TERM$	6,412
Matched with CRSP and COMPUSTAT	**3,436**

Panel B: Final Sample	
Unique Facilities	**3,436**
Unique Deals	2,101
Unique Firm-Years	2,005
Unique Firms	1,035

Table 2. Summary Statistics: Loan Terms

This table presents summary statistics on terms for my final sample of loan facilities (defined in Table 1). In this table, the unit of observation is a loan facility, so there are 3,436 observations in total. Panel A presents the percentage of loan facilities that fall into each loan type, as classified by S&P. Panels B, C, and D present summary statistics at the facility level for the interest rate spread, loan size, and loan length (respectively), proposed on the launch date. For variable definitions, see Appendix B.

Panel A: Loan Types

	Pro-Rata		*Institutional*			
	RC	TLA	TLB	TLC	TLD	SL
% of Total Observations	0.447	0.176	0.343	0.010	0.002	0.021

Panel B: *SPREAD_TALK* (in bps over LIBOR)

Facility Type	Mean	SD	5th	25th	50th	75th	95th
RC	244	98	125	175	225	300	425
TLA	237	104	125	175	225	275	400
TLB	343	135	175	262	325	400	600
TLC	323	163	191	231	275	338	684
TLD	297	76	194	275	288	338	391
SL	685	228	325	525	700	825	1,000

Panel C: *AMOUNT_TALK* (in Millions of USD)

Facility Type	Mean	SD	5th	25th	50th	75th	95th
RC	402	575	30	100	225	500	1,400
TLA	426	546	38	100	225	550	1,400
TLB	698	845	100	230	400	850	2,002
TLC	529	460	122	250	382	600	1,321
TLD	618	689	124	284	450	574	1,695
SL	250	257	32	80	180	300	720

Panel D: *TERM* (in Years)

Facility Type	Mean	SD	5th	25th	50th	75th	95th
RC	4.70	1.00	3.00	5.00	5.00	5.00	6.00
TLA	4.93	0.86	3.00	5.00	5.00	5.00	6.00
TLB	6.24	1.22	3.89	6.00	7.00	7.00	7.01
TLC	5.88	1.55	2.83	5.12	6.15	7.00	7.60
TLD	5.40	1.44	3.64	4.35	5.15	7.00	7.00
SL	6.17	1.57	3.15	5.00	6.40	7.50	8.00

Table 3. Summary Statistics: Borrower Characteristics

This table presents summary statistics of COMPUSTAT and CRSP variables for my final sample of borrowers (defined in Table 1). In this table, the unit of observation is a loan deal, so there are 2,101 observations in total. Panel A presents summary statistics for the issuer at the time of the launch (t), where COMPUSTAT data is lagged four months and CRSP data is contemporaneous. Excess returns are calculated by subtracting the market return. $t+i$ refers to i months after the loan launch. Excess Return Reversal is defined as the excess return from $t+1$ to $t+12$ minus the excess return from $t-12$ to $t-1$. Market capitalization is calculated from CRSP in Panels A and C, but calculated from COMPUSTAT in Panel B. Annualized volatility is calculated as follows. In Panel A, its the annualized standard deviation of monthly returns from $t-12$ to $t+12$. In Panel C, its the annualized standard calculated over a 24 month rolling window. Panel B (C) presents the summary statistics on the same variables as Panel A, but for the entire COMPUSTAT (CRSP) universe. All variables calculated from COMPUSTAT are winsorized at 1% – 99% within year, except market capitalization. For variable definitions, see Appendix B.

Panel A: Table 1 Final Sample

	Mean	SD	5th	25th	50th	75th	95th
Market Cap (in thousands USD)	2,807	5,001	130	509	1,267	3,094	10,425
Total Assets (in thousands USD)	5,067	15,373	242	701	1,712	4,670	18,833
D_A	0.40	0.25	0.01	0.23	0.38	0.54	0.82
ROA	0.03	0.09	-0.11	-0.00	0.03	0.07	0.15
$EBITDA\_REVT$	0.18	0.15	0.03	0.09	0.15	0.24	0.44
$CAPX\_AT$	0.06	0.08	0.01	0.02	0.04	0.07	0.19
$ACCRUALS\_AT$	-0.04	0.09	-0.16	-0.08	-0.04	-0.01	0.07
I_DIV	0.32	0.46					
$SUBDBT$	0.22	0.41					
Excess Return from $t-12$ to $t-1$	0.157	0.811	-0.539	-0.184	0.031	0.309	1.135
Excess Return from $t+1$ to $t+12$	0.055	0.537	-0.615	-0.221	-0.012	0.229	0.863
Excess Return Reversal	-0.102	0.954	-1.278	-0.405	-0.073	0.231	1.028
Annualized Volatility from $t-12$ to $t+12$	0.448	0.243	0.201	0.290	0.385	0.538	0.909

Panel B: COMPUSTAT Universe (1999 - 2018)

	Mean	SD	5th	25th	50th	75th	95th
Market Cap (in thousands USD)	3,073	16,593	2.18	26.81	148	864	11,832
Total Assets (in thousands USD)	9,470	85,133	0.81	30.05	248	1,566	21,145
D_A	0.38	1.07	0.00	0.02	0.18	0.39	0.96
ROA	-0.46	2.48	-1.65	-0.13	0.01	0.06	0.19
$EBITDA\_REVT$	-1.82	11.65	-5.29	-0.01	0.11	0.26	0.56
$CAPX\_AT$	0.07	0.14	0.00	0.00	0.02	0.07	0.27
$ACCRUALS\_AT$	-0.04	0.48	-0.39	-0.09	-0.03	0.01	0.31
I_DIV	0.28	0.45					
$SUBDBT$	0.06	0.23					

Panel C: CRSP Universe (1999 - 2018)

	Mean	SD	5th	25th	50th	75th	95th
Market Cap (in thousands USD)	3,375	16,543	11.66	77.91	322	1,429	13,099
Annualized Volatility	0.426	0.344	0.100	0.205	0.334	0.542	1.048

Table 4. Correlation Matrix: Loan Terms and Borrower Characteristics

This table presents a correlation matrix between loan terms from Table 2 and borrower characteristics from Table 3, for my final sample (Table 1). Because deals often have both pro-rata and institutional facilities, I present correlations for the two types of facilities separately. Panel A (B) presents the Pearson correlation coefficients and p-values from a test of the null hypothesis that the correlation is equal to zero in parenthesis, for the sample of pro-rata (institutional) loan facilities. There are 2,142 facilities in Panel A and 1,294 facilities in Panel B, which sum to the total of unique facilities from Table 1. For cases in which deals have multiple pro-rata and institutional facilities, this table keeps only the highest facility within pro-rata (RC) or institutional (TLB). For variable definitions, see Appendix B. Asterisk convention: *p<0.1; **p<0.05; ***p<0.01.

Panel A: Pro-Rata Facilities

	SPREAD_TALK	*AMOUNT_TALK*	*TERM*
LOG_AT	-0.181	0.571	-0.069
	(<0.001)***	(<0.001)***	(0.001)***
D_A	0.101	0.041	0.017
	(<0.001)***	(0.059)**	(0.420)
ROA	-0.193	0.013	0.057
	(<0.001)***	(0.551)	(0.008)***
EBITDA_REVT	-0.100	0.097	0.024
	(<0.001)***	(<0.001)***	(0.273)
CAPX_AT	-0.006	0.028	-0.081
	(0.782)	(0.188)	(<0.001)***
ACCRUALS_AT	-0.077	-0.016	0.023
	(<0.001)***	(0.461)	(0.292)
I_DIV	-0.129	0.142	-0.012
	(<0.001)***	(<0.001)***	(0.585)
SUBDBT	-0.011	-0.038	0.078
	(0.609)	(0.081)**	(<0.001)***

Panel B: Institutional Facilities

	SPREAD_TALK	*AMOUNT_TALK*	*TERM*
LOG_AT	-0.167	0.464	-0.040
	(<0.001)***	(<0.001)***	(0.146)
D_A	-0.012	0.079	-0.049
	(0.676)	(0.004)***	(0.081)**
ROA	-0.234	0.070	0.161
	(<0.001)***	(0.011)**	(<0.001)***
EBITDA_REVT	-0.190	0.144	0.070
	(<0.001)***	(<0.001)***	(0.012)**
CAPX_AT	0.096	0.005	-0.115
	(0.001)***	(0.847)	(<0.001)***
ACCRUALS_AT	-0.080	-0.020	0.052
	(0.004)***	(0.469)	(0.062)**
I_DIV	-0.106	0.137	0.020
	(<0.001)***	(<0.001)***	(0.481)
SUBDBT	-0.138	-0.073	0.008
	(<0.001)***	(0.009)***	(0.782)

Table 5. Fama-MacBeth Regressions: Hypothesis 1

This table presents results of monthly Fama and MacBeth (1973) regressions of borrowers' equity returns on the loan term residuals from Section 4, controlling for other factors that are known to determine the cross-section of equity returns. The predicted signs by Hypothesis 1 are presented at the bottom of the table. Reported coefficients are multiplied by 100 and t-statistics are reported in brackets. Standard errors used to calculate t-statistics are calculated from the time-series of twelve coefficient estimates, without adjusting for serial correlation. In Panel A, Fama-MacBeth regressions are performed monthly in event-time over the twelve months following the loan launch, where $t = 0$ corresponds to the loan launch date for each loan. In Panel B, Fama-MacBeth regressions are performed monthly in event-time over the twelve months preceding the loan launch. Book-to-market (BTM)is calculated as described in Appendix B. Market capitalization is lagged 6 months, including in the calculation of book-to-market. Natural logs of book-to-market and market cap are used in these regressions. Gross profit is scaled by total assets, following Novy-Marx (2013). $\text{Return}_{t,t+1}$ is the return on the borrower's equity from month t to $t+1$. $SPREAD\_RES$, $AMOUNT\_RES$, $TERM\_RES$, and $COMB\_RES$ are calculated following the methodology described in Section 4. Observations without a strictly positive value of book equity are dropped. Observations with missing values of these variables of interest are dropped. Panel A (B) has a minimum of 1618 (1721) observations in a cross-sectional regression at $t = 12$ ($t = -12$). Intercepts were included in estimations, but are omitted from the table for brevity. All independent variables, except $SPREAD\_RES$, $AMOUNT\_RES$, $TERM\_RES$, and $COMB\_RES$, are winsorized at 1%-99% by year.

Panel A: Monthly Regressions from $t = 1$ to $t = 12$

	Dependent variable = $\text{Return}_{t,t+1}$					
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Book-to-market	0.233	0.211	0.234	0.205	0.193	0.206
	⟨2.197⟩	⟨2.042⟩	⟨2.215⟩	⟨1.921⟩	⟨1.860⟩	⟨1.971⟩
Market cap	-0.204	-0.181	-0.186	-0.161	-0.138	-0.142
	⟨-2.203⟩	⟨-1.941⟩	⟨-1.907⟩	⟨-1.703⟩	⟨-1.373⟩	⟨-1.418⟩
Gross profit	0.552	0.611	0.586	0.459	0.537	0.622
	⟨0.893⟩	⟨0.981⟩	⟨0.959⟩	⟨0.736⟩	⟨0.865⟩	⟨1.004⟩
$\text{Return}_{t-1,t}$	3.929	3.896	3.924	3.906	3.892	3.866
	⟨4.276⟩	⟨4.235⟩	⟨4.307⟩	⟨4.296⟩	⟨4.305⟩	⟨4.254⟩
$\text{Return}_{t-12,t-2}$	0.510	0.511	0.506	0.502	0.501	0.495
	⟨1.835⟩	⟨1.815⟩	⟨1.810⟩	⟨1.770⟩	⟨1.750⟩	⟨1.729⟩
$SPREAD\_RES$		0.180			0.132	
		⟨2.253⟩			⟨1.692⟩	
$AMOUNT\_RES$			-0.081		-0.051	
			⟨-1.283⟩		⟨-0.902⟩	
$TERM\_RES$				-0.363	-0.320	
				⟨-2.264⟩	⟨-2.066⟩	
$COMB\_RES$						-0.133
						⟨-2.527⟩
Hypothesis 1:		(+)	(−)	(−)		(−)

Panel B: Monthly Regressions from $t = -12$ to $t = -1$

	Dependent variable = $\text{Return}_{t,t+1}$					
Independent variable	(7)	(8)	(9)	(10)	(11)	(12)
Book-to-market	0.123	0.187	0.123	0.153	0.200	0.175
	⟨0.554⟩	⟨0.871⟩	⟨0.555⟩	⟨0.696⟩	⟨0.930⟩	⟨0.802⟩
Market cap	-1.020	-1.075	-1.079	-1.110	-1.176	-1.187
	⟨-8.777⟩	⟨-9.686⟩	⟨-8.627⟩	⟨-9.632⟩	⟨-9.780⟩	⟨-10.345⟩
Gross profit	-1.086	-1.097	-1.187	-0.880	-1.008	-1.173
	⟨-2.036⟩	⟨-2.064⟩	⟨-2.261⟩	⟨-1.664⟩	⟨-1.942⟩	⟨-2.190⟩
$\text{Return}_{t-1,t}$	2.409	2.110	2.352	2.051	1.852	2.000
	⟨2.774⟩	⟨2.475⟩	⟨2.675⟩	⟨2.375⟩	⟨2.150⟩	⟨2.282⟩
$\text{Return}_{t-12,t-2}$	-0.019	-0.189	-0.040	-0.136	-0.262	-0.213
	⟨-0.088⟩	⟨-0.928⟩	⟨-0.182⟩	⟨-0.646⟩	⟨-1.283⟩	⟨-1.003⟩
$SPREAD\_RES$		-0.563			-0.454	
		⟨-4.386⟩			⟨-3.719⟩	
$AMOUNT\_RES$			0.233		0.170	
			⟨3.994⟩		⟨2.636⟩	
$TERM\_RES$				0.833	0.640	
				⟨6.184⟩	⟨5.009⟩	
$COMB\_RES$						0.365
						⟨7.237⟩
Hypothesis 1:		(−)	(+)	(+)		(+)

Table 6. Equity Mispricing Tests: Hypothesis 1

This table presents cross-sectional OLS regressions of the four loan term residuals from Section 4 onto four proxies four equity mispricing, discussed in Section 5.1 and defined in Appendix B. The predicted signs by Hypothesis 1 are presented at the bottom of the table. The difference between each Panel is the dependent variable used in the regression, indicated at the top of the table. Subscripts on independent variables refer to the time at which they are measured, where $t = 0$ corresponds to the month of the loan launch. Excess returns are calculated by subtracting the market return. Intercepts were included in all estimations, but were omitted from the table for brevity. The sample used in this estimation is the same as Table 5, where changes in the number of observations reflet data availability. Standard errors are calculated following White (1980). Asterisk convention: *p<0.1; **p<0.05; ***p<0.01.

Panel A: Dependent variable = $SPREAD\_RES$				
$\text{ExReturn}_{1,12}$ $-\text{ExReturn}_{-12,-1}$	0.106** (0.053)			
BTM_{-1}		0.317*** (0.060)		
BTM_{12} $-BTM_{-1}$			−0.079* (0.047)	
VAL_{-1}				−0.135*** (0.033)
Hypothesis 1:	(+)	(+)	(−)	(−)
Observations	2,034	1,819	1,560	1,681
R^2	0.005	0.057	0.005	0.010
Intercept	✓	✓	✓	✓

Panel B: Dependent variable = $AMOUNT\_RES$				
$\text{ExReturn}_{1,12}$ $-\text{ExReturn}_{-12,-1}$	−0.015 (0.028)			
BTM_{-1}		−0.042 (0.041)		
BTM_{12} $-BTM_{-1}$			0.010 (0.031)	
VAL_{-1}				0.091** (0.036)
Hypothesis 1:	(−)	(−)	(+)	(+)
Observations	2,034	1,819	1,560	1,681
R^2	0.0001	0.001	0.0001	0.003
Intercept	✓	✓	✓	✓

Panel C: Dependent variable = $TERM\_RES$				
$\text{ExReturn}_{1,12}$ $-\text{ExReturn}_{-12,-1}$	−0.034 (0.035)			
BTM_{-1}		−0.190*** (0.033)		
BTM_{12} $-BTM_{-1}$			0.073** (0.033)	
VAL_{-1}				0.063*** (0.024)
Hypothesis 1:	(−)	(−)	(+)	(+)
Observations	2,034	1,819	1,560	1,681
R^2	0.001	0.041	0.006	0.004
Intercept	✓	✓	✓	✓

Panel D: Dependent variable = $COMB\_RES$				
$\text{ExReturn}_{1,12}$ $-\text{ExReturn}_{-12,-1}$	−0.157* (0.087)			
BTM_{-1}		−0.553*** (0.091)		
BTM_{12} $-BTM_{-1}$			0.171** (0.076)	
VAL_{-1}				0.288*** (0.061)
Hypothesis 1:	(−)	(−)	(+)	(+)
Observations	2,034	1,819	1,560	1,681
R^2	0.003	0.050	0.006	0.012
Intercept	✓	✓	✓	✓

Table 7. Disclosure Quality Tests: Hypothesis 2

This table presents cross-sectional OLS regressions of the four loan term residuals from Section 4 onto four measures of equity mispricing and DQ_DEMEAN, which is DQ from Chen et al. (2015) demeaned by year (Appendix B). The predicted signs on the interaction term by Hypothesis 2 are indicated in each Panel. $EQ\_MISPRICING$ refers to one of the four measures of equity mispricing, indicated at the bottom of the table. The difference between the Panels is the dependent variable in the regression, indicated at the top of the table. The unlabeled table at the bottom portion of the page presents information relevant to that column in all Panels. The sample used in this table is the same as Table 6, minus observations with a missing DQ_DEMEAN. For variable definitions, see Appendix B. Subscripts on independent variables refer to the time at which they are measured, where $t = 0$ corresponds to the month of the loan launch. Intercepts are included in all regressions, but omitted from the table for brevity. Results with $COMB\_RES$ are omitted for brevity, but the conclusions are the same as Panels A and C. Asterisk convention: *p<0.1; **p<0.05; ***p<0.01.

Panel A: Dependent variable = $SPREAD\_RES$				
$EQ\_MISPRICING$	0.176***	0.303***	-0.084**	−0.127***
	(0.044)	(0.037)	(0.033)	(0.042)
DQ_DEMEAN_{-1}	-1.255*	-0.142	-0.128	-1.034
	(0.655)	(0.804)	(0.619)	(0.685)
$EQ\_MISPRICING * DQ\_DEMEAN_{-1}$	-1.117**	-0.774	-0.098	0.640
	(0.557)	(0.709)	(0.605)	(0.708)
Hypothesis 2:	(-)	(-)	(+)	(+)
Adjusted R^2	0.012	0.055	0.004	0.008
Panel B: Dependent variable = $AMOUNT\_RES$				
$EQ\_MISPRICING$	0.015	-0.075**	0.004	0.127***
	(0.046)	(0.038)	(0.034)	(0.042)
DQ_DEMEAN_{-1}	0.289	0.715	-0.197	-0.087
	(0.698)	(0.828)	(0.641)	(0.676)
$EQ\_MISPRICING * DQ\_DEMEAN_{-1}$	-0.144	-0.808	0.433	-0.652
	(0.594)	(0.730)	(0.627)	(0.699)
Hypothesis 2:	(+)	(+)	(-)	(-)
Adjusted R^2	-0.002	0.001	-0.002	0.005
Panel C: Dependent variable = $TERM\_RES$				
$EQ\_MISPRICING$	-0.109***	-0.161***	0.051**	0.068**
	(0.029)	(0.025)	(0.025)	(0.028)
DQ_DEMEAN_{-1}	1.916***	0.974*	1.852***	1.704***
	(1.281)	(1.593)	(1.256)	(1.288)
$EQ\_MISPRICING * DQ\_DEMEAN_{-1}$	0.977***	0.358	-0.421	-0.127
	(0.367)	(0.487)	(0.456)	(0.477)
Hypothesis 2:	(+)	(+)	(-)	(-)
Adjusted R^2	0.022	0.039	0.016	0.015

$EQ\_MISPRICING$ measure (Panels A-D)	$\text{ExReturn}_{1,12}-\text{ExReturn}_{-12,-1}$	BTM_{-1}	$BTM_{12} - BTM_{-1}$	VAL_{-1}
Observations (Panels A-D)	1,377	1,285	1,058	1,183
Intercept included (Panels A-D)	✓	✓	✓	✓

Table 8. Disclosure Quantity Tests: Hypothesis 3

This table presents cross-sectional OLS regressions of the four loan term residuals from Section 4 onto four measures of equity mispricing and $\Delta ln(1+GUIDANCE)_{-1}$, which is the change in the natural logarithm of one plus the number of management forecasts issued by a firm in the quarter prior to the loan launch relative to the same quarter of the prior year, from I/B/E/S (Appendix B). The predicted signs on the interaction term by Hypothesis 3 are indicated in each Panel. $EQ\_MISPRICING$ refers to one of the four measures of equity mispricing, indicated at the bottom of the table. The difference between the Panels is the dependent variable in the regression, indicated at the top of the table. The unlabeled table at the bottom portion of the page presents information relevant to that column in all Panels. The sample used in this table is the same as Table 6. For variable definitions, see Appendix B. Subscripts on independent variables refer to the time at which they are measured, where $t = 0$ corresponds to the month of the loan launch. Intercepts are included in all regressions, but are omitted from the table for brevity. Results with $COMB\_RES$ are omitted for brevity. Asterisk convention: *p<0.1; **p<0.05; ***p<0.01.

Panel A: Dependent variable = $SPREAD\_RES$				
$EQ\_MISPRICING$	0.130**	0.313***	0.038	-0.145***
	(0.056)	(0.060)	(0.045)	(0.034)
$\Delta ln(1+GUIDANCE)_{-1}$	-0.178***	-0.121*	-0.106**	-0.165***
	(0.047)	(0.067)	(0.046)	(0.048)
$EQ\_MISPRICING * \Delta ln(1+GUIDANCE)_{-1}$	-0.124*	-0.045	-0.066	0.102**
	(0.070)	(0.082)	(0.067)	(0.053)
Hypothesis 3:	(-)	(-)	(+)	(+)
Adjusted R^2	0.013	0.063	0.004	0.019
Panel B: Dependent variable = $AMOUNT\_RES$				
$EQ\_MISPRICING$	-0.006	-0.042	-0.001	0.089**
	(0.033)	(0.041)	(0.030)	(0.038)
$\Delta ln(1+GUIDANCE)_{-1}$	-0.160**	-0.194**	-0.039	-0.170**
	(0.066)	(0.082)	(0.052)	(0.069)
$EQ\_MISPRICING * \Delta ln(1+GUIDANCE)_{-1}$	-0.061	0.028	0.108	-0.009
	(0.047)	(0.067)	(0.068)	(0.072)
Hypothesis 3:	(+)	(+)	(-)	(-)
Adjusted R^2	0.004	0.006	0.002	0.008
Panel C: Dependent variable = $TERM\_RES$				
$EQ\_MISPRICING$	-0.056*	-0.187***	-0.015	0.067***
	(0.034)	(0.035)	(0.027)	(0.024)
$\Delta ln(1+GUIDANCE)_{-1}$	-0.019	-0.085**	-0.015	-0.041
	(0.032)	(0.038)	(0.035)	(0.032)
$EQ\_MISPRICING * \Delta ln(GUIDANCE)_{-1}$	0.085*	0.064	0.046	-0.056*
	(0.049)	(0.041)	(0.058)	(0.034)
Hypothesis 3:	(+)	(+)	(-)	(-)
Adjusted R^2	0.003	0.043	-0.004	0.004

$EQ\_MISPRICING$ measure (Panels A-D)	$\text{ExReturn}_{1,12}-\text{ExReturn}_{-12,-1}$	BTM_{-1}	$BTM_{12}-BTM_{-1}$	VAL_{-1}
Observations	2,034	1,819	1,560	1,681
Intercept included (Panels A-D)	✓	✓	✓	✓

Table 9. Asymmetry of Effect Tests: Distinguishing between Mechanisms for Hypothesis 1

This table presents cross-sectional OLS regressions of $COMB\_RES$ onto four measures of equity mispricing, and a dummy variable ($I\_UNDERPRICED$) for if these measures suggest the borrower's equity is underpriced. $EQ\_MISPRICING$ refers to one of the four measures of equity mispricing, indicated at the bottom of the table. $I\_UNDERPRICED$ is an indicator variable that equals 1 if the corresponding $EQ\_MISPRICING$ measure indicates underpricing, relative to its median in my sample. Panel A presents the regression results, while Panel B presents the estimates of the coefficients on $EQ\_MISPRICING$ from Table 6 for comparison. Only estimations using $COMB\_RES$ are presented for brevity; results using $SPREAD\_RES$ and $TERM\_RES$ present the same interpretation. Under the coefficient of interest (the interaction term), the table indicates the predictions of my two mechanisms: cross-market learning and hold-up. The sample used in this table is the same as Table 6. For variable definitions, see Appendix B. Subscripts on independent variables refer to the time at which they are measured, where $t = 0$ corresponds to the month of the loan launch. Intercepts were included in all estimations, but were omitted for brevity. Asterisk convention: *p<0.1; **p<0.05; ***p<0.01.

Panel A: Dependent variable = $COMB\_RES$				
$EQ\_MISPRICING$	0.266***	-0.896	-0.143*	0.090**
	(0.072)	(0.567)	(0.077)	(0.040)
$I\_UNDERPRICED$	-0.240*	-0.635***	-0.248**	-1.728***
	(0.132)	(0.225)	(0.118)	(0.503)
$EQ\_MISPRICING * I\_UNDERPRICED$	-1.165***	0.473	0.797***	0.435**
	(0.194)	(0.575)	(0.154)	(0.188)
Cross-market learning prediction:	(?)	(?)	(?)	(?)
Hold-up problem prediction:	(-)	(-)	(+)	(+)
$EQ\_MISPRICING$ measure	$\text{ExReturn}_{1,12} - \text{ExReturn}_{-12,-1}$	BTM_{-1}	$BTM_{12} - BTM_{-1}$	VAL_{-1}
$I\_UNDERPRICED = 1$ if $EQ\_MISPRICING$	> median	> median	< median	< median
Observations	2,034	1,819	1,560	1,681
Adjusted R^2	0.033	0.057	0.034	0.053
Intercept included	✓	✓	✓	✓

Panel B: Results from Table 6				
$EQ\_MISPRICING$ coefficient in Panel D	-0.157	-0.533	0.171	0.288
Hypothesis 1:	(-)	(-)	(+)	(+)

Table 10. Loan Facility Type Tests: Distinguishing between Mechanisms for Hypothesis 1

This table presents cross-sectional OLS regressions of $COMB\_RES$ onto four measures of equity mispricing, by loan type. $COMB\_RES$ in this table is different from $COMB\_RES$ in other tables of this paper. In Panel A (B), it is generated using the methodology in Section 4 on *only* pro-rata (institutional term loan) facilities in my sample. The total number of observations in Panels A and B sum to more than the number of observations in Table 6 because less facilites are dropped in the final step of the methodology in Section 4 - most deals only have one facility within the pro-rata or institutional pieces of the loan. Panels A and B presents the regression results, while Panel C presents the estimates of the coefficients on the same variables from Table 6 for comparison. Only estimations using $COMB\_RES$ are presented for brevity; results using $SPREAD\_RES$ and $TERM\_RES$ present the same interpretation. The sample used in this table is the same as Table 6. For variable definitions, see Appendix B. Subscripts on independent variables refer to the time at which they are measured, where $t = 0$ corresponds to the month of the loan launch. Intercepts were included in all estimations, but were omitted for brevity. Asterisk convention: *p<0.1; **p<0.05; ***p<0.01.

Panel A: Pro-Rata Facilities: (RC, TLA)				
	Dependent variable = $COMB\_RES$			
$\text{ExReturn}_{1,12} - \text{ExReturn}_{-12,-1}$	−0.082			
	(0.078)			
BTM_{-1}		−0.351***		
		(0.074)		
$BTM_{12} - BTM_{-1}$			0.137*	
			(0.079)	
VAL_{-1}				0.160***
				(0.026)
Observations	1,554	1,420	1,234	1,313
R^2	0.001	0.029	0.006	0.030
Intercept included	✓	✓	✓	✓

Panel B: Institutional Term Loans: (TLB, TLC, TLD)				
	Dependent variable = $COMB\_RES$			
$\text{ExReturn}_{1,12} - \text{ExReturn}_{-12,-1}$	−0.123			
	(0.087)			
BTM_{-1}		−0.513***		
		(0.127)		
$BTM_{12} - BTM_{-1}$			0.180*	
			(0.108)	
VAL_{-1}				0.211***
				(0.035)
Observations	1,168	1,031	838	948
R^2	0.003	0.059	0.009	0.048
Intercept included	✓	✓	✓	✓

Panel C: Results from Table 6				
Coefficient in Table 6 Panel D	−0.157	−0.533	0.171	0.288

Appendix A. Information in S&P LCD Database

This appendix presents the list of information provided for each observation in the S&P LCD database. Panel A lists the information that varies at the deal-level. Panel B lists the information that varies at the facility-level.

Panel A: Deal-Level Information
Company name of borrower
Date on which loan was launched (i.e. initial talk terms set)
Deal sponsor
Industry of borrower
Borrower's home country
Lead arranger name
Borrower company description
Borrower ticker
Purpose for loan deal
Rating of loan facility by Standard and Poor's
Rating of loan facility by Moody's
Rating of borrower by Standard and Poor's at time of issuance
Rating of borrower by Moody's at time of issuance
Standard and Poor's default recovery rating
Indicator variable for if the loan was covenant-lite
Indicator variable for if the loan was asset-backed
Total amount of capital raised in deal
Amount of new capital raised
Amount of new capital invested in institutional loan tranches
Amount of new capital invested in pro-rata loan tranches

Panel B: Facility-Level Information
Facility type (RC, TLA, TLB, TLC, TLD, SL)
Date on which loan size was flexed
Amount of loan size flex
Final size of loan facility
Date on which loan spread was flexed
Lower range of talk spread
Upper range of talk spread
Amount of loan spread flex
Final interest rate spread of loan facility (over LIBOR) in basis points
Term (length) of loan facility
Amount of LIBOR floor flex
Final facility LIBOR floor
Date of OID flex
OID flex amount
Final OID
Date at which loan began trading in the secondary market
Price at which loan begain trading in secondary market

Appendix B. Variable Definitions

This appendix contains the list of variable names that are used in this paper and their corresponding descriptions. Variables are broken up in two tables based on the data source from which they are calculated. COMPUSTAT variable names are provided in parenthesis in the variable descriptions for variables calculated from COMPUSTAT.

Variable Name	Variable Description
Calculated from LCD	
SPREAD_TALK	This variable corresponds to interest rate spread that that was proposed by the lead arranger on the launch date for a given loan facility. It is calculated by taking the final spread for the facility in LCD and subtracting the spread flex. If the spread flex is missing, then I take the midpoint of the lower and upper range of the talk spread.
AMOUNT_TALK	This variable corresponds to the size of the loan facility that was proposed by the lead arranger on the launch date. It is calculated by subtracting size flex from the final loan size in LCD.
TERM	This variable corresponds to the length of the loan facility. There are not flexed, so I can use the final term provided by LCD
SP_CCR	Categorical variable that equals 1 if the firm is not rated by S&P, equals 23 if firm is rated AAA (highest rating), and decreases by 1 for each rating below AAA. This variable can take any value between 1 and 23, with a higher value indicating a higher credit rating.
NR	Indicator variable that equals 1 if borrower was not rated by S&P.
PR	Indicator variable that equals 1 if the loan facility type is RC or TLA.
INST_TL	Indicator variable that equals 1 if the loan facility type is TLB, TLC, or TLD.
SL	Indicator variable that equals 1 if the loan facility type is Second-Lien (SL).
Calculated from COMPUSTAT	
LOG_AT	Log of total assets (AT)
D_A	Total long term debt (DLTT) plus debt due within a year and notes payable due within a year (DLC), divided by total assets.
ROA	Net income (IB) in year t, divided by total assets (AT) in year $t-1$.
EBITDA_REVT	EBITDA (EBITDA) divided by revenue (REVT).
CAPX_AT	Capital expenditures (CAPX) in year t divided by total assets in year $t-1$.
ACCRUALS_AT	Change in current assets (ACT) minus change in cash (CH) - change in current liabilities (LCT) + change in debt in current liabilities (DLC) + change in income taxes payable (TXP) - depreciation (DP), where all changes occur between year t and $t-1$, divided by total assets in year $t-1$. This calculation follows (Sloan (1996), Ball et al. (2016)).
I_DIV	Indicator variable that equals 1 if dividends paid on common stock (DVC) were greater than zero.
SUBDBT	Indicator variable that equals 1 if the firm has subordinated debt (DS).
F_SCORE	Piotroski F-Score, calculated following Piotroski (2000).
DQ_DEMEAN	Disaggregation quality, calculated following Chen et al. (2015), de-meaned cross-sectionally by year using mean from entire COMPUSTAT sample.

Appendix B. Variable Definitions (Continued)

Variable Name	**Variable Description**
Calculated from CRSP and COMPUSTAT	
Book-to-market (BTM)	Book equity calculated from COMPUSTAT divided by market capitalization calculated from CRSP. Book equity is calculated as follows. Stockholder's equity + balance sheet deferred taxes (TXDB) + balance sheet investment tax credits (ITCB) - preferred stock, where balance sheet deferred taxes and investment tax credits are set equal to zero if they are missing. Stockholder's equity is calculated as follows: Equals stockholder's equity (SEQ), if available. Else, equals common & ordinary equity (CEQ), if available. Else, equals total assets (AT) minus total liabilities (LT). Preferred stock is calculated as follows: Equals preferred stock redemption value (PSTKRV), if available. Else, equals liquidation value (PSTKL). Else, equals carrying value (PSTK), if available. This calculation follows Ball et al. (2016).
VAL	The difference between the a firm's market-to-book ($^1/_{BTM}$) tercile and F_SCORE tercile. I define market-to-book terciles as follows: a firm is in the first (second) [third] tercile if it's market-to-book is below the 33rd percentile (between 33rd and 67th percentiles) [above 67th percentile] of market-to-book in my sample. F_SCORE terciles are defined following Piotroski and So (2012): a firm is in the first (second) [third] tercile if it's F_SCORE is 1, 2, or 3 (4, 5, 6) [7, 8, 9].
$EQ\_MISPRICING$	A measure of equity mispricing, that will be specified in the a row in whatever table it's in. There are measures of equity mispricing I use, which are shown in Table 6.
$I\_UNDERPRICED$	An indicator variable for if a measure of equity mispricing indicates a borrower's equity is underpriced. This equals 1 if the borrower's measure of equity mispricing is above or below the median value in my sample (depending on the measure), which will be specified in the table of results.
Calculated from I/B/E/S	
$\Delta ln(1+GUIDANCE)_t$	The change in the natural logarithm of one plus the total number of management forecasts for a given firm between the quarter in which month t is in, and the quarter in which month $t-12$ is in. A borrower is assumed to issue zero management forecasts in a quarter if there is no data in I/B/E/S.

Appendix C. Merging LCD with CRSP and COMPSUTAT

This appendix provides a detailed description of how I merged the remaining 6,412 facility level observations from Table 1 Panel A to the CRSP monthly stock file (MSF) and the COMPUSTAT annual fundamental file (FUNDA), and the data restrictions imposed. Variable definitions are in Appendix B. The procedure is as follows:

1. Observations were matched with the CRSP .msenames file to obtain PERMNOs on the following criteria:
   (a) Exact ticker match
   (b) Loan launch date is after CRSP beginning effective link date (NAMEDT)
   (c) Loan launch date is before CRSP ending effective link date (NAMENDT)
   (d) CRSP share code (SHRCD) indicates the PERMNO corresponds to an ordinary equity security (10, 11, or 12)
2. Every match was checked manually by Google searching the company name and ensuring that the company traded under that ticker during the launch date. 91 facility-level observations were deleted because of a bad match.
3. The remaining matches were linked to GVKEYs by PERMNOs, via the CCM linking table.
4. The remaining data was matched with COMPUSTAT on GVKEY and with CRSP on PERMNO, ensuring that the COMPUSTAT data collection date (DATADATE) was in the interval of CCM effective link dates (ULINKDT, ULINKENDT). COMPUSTAT data is lagged 4 months with respect to CRSP data. The following data restrictions were imposed:
   (a) Non-missing values of variables in Appendix B
   (b) Non-missing sequence of CRSP returns for at least one month following the loan launch

Appendix D. Regression of Loan Terms onto Borrower Characteristics: Full Sample

This table presents results from three separate regressions of loan spreads, sizes, and lengths onto various borrower characteristics for my sample of loan facilities from LCD. This corresponds to estimation of Equations (1), (2), and (3) via OLS, on my full sample from Table 1, using the choice X_b specified in Equation (4). Standard errors in parenthesis are presented below coefficients estimates and are calculated following White (1980). As indicated in the table, all independent variables are standardized to have zero mean and unit variance prior to the estimation to ease interpretation. Loan type dummies are included (PR_i, $INST\_TL_i$, and SL_i from Section 4), but coefficients are omitted for brevity. For variable definitions see Appendix B. Asterisk convention: *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable		
Independent variable	*SPREAD_TALK*	*AMOUNT_TALK*	*TERM*
LOG_AT	−9.524	258.805	−0.095
	(1.812)***	(15.863)***	(0.018)***
D_A	0.101	10.159	−0.017
	(2.244)	(11.283)	(0.021)
ROA	−13.846	59.922	0.093
	(3.549)***	(11.950)***	(0.025)***
EBITDA_REVT	−10.453	26.286	0.039
	(3.440)***	(11.780)**	(0.022)*
CAPX_AT	1.890	21.956	−0.103
	(2.003)	(9.916)**	(0.026)***
ACCRUALS_AT	−2.019	−18.259	−0.020
	(2.377)	(10.848)*	(0.022)
I_DIV	−4.972	41.623	−0.017
	(3.814)	(24.065)*	(0.041)
SUBDBT	−23.761	−95.141	0.097
	(4.299)***	(26.436)***	(0.047)**
SP_CCR	−27.067	14.106	0.031
	(1.711)***	(9.790)	(0.018)*
NR	−261.615	154.318	−0.212
	(19.321)***	(91.237)*	(0.190)
Loan type dummies	✓	✓	✓
Independent variables standardized	✓	✓	✓
R^2	0.890	0.555	0.963
Adjusted R^2	0.889	0.553	0.963
Observations	3,436	3,436	3,436

Appendix E. Residual Summary Statistics

This table presents summary statistics on the set of residuals that are used in all of my tests. The methodology I use to generate these residuals is described in Section 4, and these residuals are used in Tables 5, 6, 7, 8, and 9. Importantly, these residuals are calculated using information available to market participants in real-time. The sample in this table corresponds to my final sample of loan deals from Table 1, expect I drop loans launched prior to January 1st, 2000 to ensure enough observations were available in the estimation procedure described in Section 4. Panel A presents univariate summary statistics. Panel B presents the Pearson correlation coefficients and p-values from a test of the null hypothesis that the correlation is equal to zero in parenthesis, between the three residuals. Panels C and D present the results from a singular value decomposition of a matrix containing these three residuals as column vectors. There are 2,034 observations summarized in this table, corresponding to the number of loan deals from Table 1 minus the deals originated prior to January 1st, 2000. Asterisk convention: *p<0.1; **p<0.05; ***p<0.01.

Panel A: Summary Statistics

	Mean	SD	5th	25th	50th	75th	95th
SPREAD_RES	0.083	1.374	-1.596	-0.770	-0.184	0.772	2.305
AMOUNT_RES	0.226	1.473	-1.134	-0.511	-0.064	0.512	2.439
TERM_RES	0.122	0.942	-1.665	-0.323	0.345	0.735	1.257
COMB_RES	0.265	2.507	-3.481	-1.164	0.512	1.556	3.696

Panel B: Correlation Matrix

	SPREAD_RES	*AMOUNT_RES*	*TERM_RES*
SPREAD_RES		-0.050	-0.267
		(0.024)**	(< 0.001)***
AMOUNT_RES			0.181
			(< 0.001)***

Panel C: PCA Loadings

	Principle component:		
Variable:	1	2	3
SPREAD_RES	-0.433	0.859	0.275
SIZE_RES	0.863	0.482	-0.149
TERM_RES	0.260	-0.173	0.950
Correlation with *COMB_RES*	0.913	-0.314	0.176

Panel D: PCA Variance

	1	2	3
Cumulative variance	0.464	0.849	1.000

References

Acharya, Viral V. and Timothy C. Johnson (2007), "Insider trading in credit derivatives." *Journal of Financial Economics*, 84, 110–141.

Addoum, Jawad M. and Justin Murfin (2019), "Equity Price Discovery with Informed Private Debt." *Review of Financial Studies*, Forthcoming.

Adrian, Tobias, Erkko Etula, and Tyler Muir (2014), "Financial Intermediaries and the Cross-Section of Asset Returns." *Journal of Finance*, 69, 2557–2596.

Aghion, Philippe and Patrick Bolton (1992), "Incomplete Approach to Contracts Financial Contracting." *The Review of Economic Studies*, 59, 473–494.

Armstrong, Christopher S, Wayne R Guay, and Joseph P Weber (2010), "The Role of Information and Financial Reporting in Corporate Governance and Debt Contracting." *Journal of Accounting and Economics*, 50, 179–234.

Baginski, Stephen P, Edward J Conrad, and John M Hassell (1993), "The Effects of Management Forecast Precision on Equity Pricing and on the Assessment of Earnings Uncertainty." *The Accounting Review*, 68, 913–927.

Baker, Malcolm, Jeremy C Stein, and Jeffrey Wurgler (2003), "When does the market matter? Stock prices and the investment of equity-dependent firms." *Quarterly Journal of Economics*, 118, 969–1005.

Ball, Ray, Joseph Gerakos, Juhani T. Linnainmaa, and Valeri Nikolaev (2016), "Accruals, cash flows, and operating profitability in the cross section of stock returns." *Journal of Financial Economics*, 121, 28–45.

Ball, Ryan, Robert M. Bushman, and Florin P. Vasvari (2008), "The Debt-Contracting Value of Accounting Information and Loan Syndicate Structure." *Journal of Accounting Research*, 46, 247–287.

Barth, Mary E, Leslie D Hodder, and Stephen H Stubben (2008), "Fair Value Accounting for Liabilities and Own Credit Risk." *The Accounting Review*, 83, 629–664.

Batta, George Eli, Jiaping Qiu, and Fan Yu (2016), "Credit derivatives and analyst behavior." *The Accounting Review*, 91, 1315–1343.

Beaver, William, Maria Correia, and Maureen F Mcnichols (2012), "Do differences in financial reporting attributes impair the predictive ability of financial ratios for bankruptcy?" *Review of Accounting Studies*, 17, 969–1010.

Beaver, William, Maureen McNichols, and Richard Price (2007), "Delisting returns and their effect on accounting-based market anomalies." *Journal of Accounting and Economics*, 43, 341–368.

Beneish, M. D., C. M.C. Lee, and D. C. Nichols (2015), "In short supply: Short-sellers and stock returns." *Journal of Accounting and Economics*, 60, 33–57.

Berger, Philip G and Rebecca N Hann (2007), "Segment Profitability and the Proprietary and Agency Costs of Disclosure." *The Accounting Review*, 82, 869–906.

Bharath, Sreedhar T, Sandeep Dahiya, Anthony Saunders, and Anand Srinivasan (2009), "Lending Relationships and Loan Contract Terms." *Review of Financial Studies*, 24, 1141–1204.

Bharath, Sreedhar T, Jayanthi Sunder, and Shyam V Sunder (2008), "Accounting Quality and Debt Contracting." *The Accounting Review*, 83, 1–28.

Blackwell, David (1951), "Comparison of Experiments." In *Proceedings of the Second Berkeley Symposium in Mathematical Statistics and Probability* (J. Neyman, ed.), 93–103, University of California Press, Berkeley and Los Angeles.

Bond, Philip, Alex Edmans, and Itay Goldstein (2012), "The Real Effects of Financial Markets." *Annual Review of Financial Economics*, 4, 339–360.

Boot, Arnold W. A. and Anjan V. Thakor (1997), "Financial System Architecture." *The Review of Financial Studies*, 10, 693–733.

Boot, Arnoud W.A. (2000), "Relationship Banking: What Do We Know?" *Journal of Financial Intermediation.*

Bruche, Max, Frederic Malherbe, and Ralf R. Meisenzahl (2017), "Pipeline Risk in Leveraged Loan Syndication."

Brunnermeier, Markus K and Stefan Nagel (2004), "Hedge Funds and the Techonology Bubble." *Journal of Finance*, 59, 2013–2040.

Bushman, Robert M., Abbie J. Smith, and Regina Wittenberg-Moerman (2010), "Price discovery and dissemination of private information by loan syndicate participants." *Journal of Accounting Research*, 48, 921–972.

Bushman, Robert M., Christopher D. Williams, and Regina Wittenberg-Moerman (2017), "The Informational Role of the Media in Private Lending." *Journal of Accounting Research*, 55, 115–152.

Calomiris, Charles W, Mauricio Larrain, Sergio L Schmukler, and Tomas Williams (2019), "Search for Yield in Large International Corporate Bonds: Investor Behavior and Firm Responses."

Campbell, John Y, Jens Hilscher, and Jan Szilagyi (2008), "In Search of Distress Risk." *Journal of Finance*, 63, 2899–2940.

Chen, Qi, Itay Goldstein, and Wei Jiang (2007), "Price Informativeness and Investment Sensitivity to Stock Price." *Review of Financial Studies*, 20, 619–650.

Chen, Shuping, Bin Miao, and Terry Shevlin (2015), "A New Measure of Disclosure Quality: The Level of Disaggregation of Accounting Data in Annual Reports." *Journal of Accounting Research*, 53, 1017–1054.

Christensen, Hans B., Valeri V. Nikolaev, and Regina Wittenberg-Moerman (2016), "Accounting Information in Financial Contracting: The Incomplete Contract Theory Perspective." *Journal of Accounting Research*, 54.

Clement, Michael, Richard Frankel, and Jeffrey Miller (2003), "Forecasts , Earnings Uncertainty , and Stock Returns." *Journal of Accounting Research*, 41, 653–679.

Cohen, Lauren and Andrea Frazzini (2008), "Economic Links and Predictable Returns." *Journal of Finance*, 1977–2011.

Cohen, Lauren and Dong Lou (2012), "Complicated firms." *Journal of Financial Economics*, 104, 383–400.

Coval, Joshua and Erik Stafford (2007), "Asset fire sales (and purchases) in equity markets." *Journal of Financial Economics*, 86, 479–512.

Cutler, David M., James M. Porteba, and Lawrence H Summers (1988), "What Moves Stock Prices?" *Journal of Portfolio Managment*.

De Franco, Gus, Florin P. Vasvari, and Regina Wittenberg-Moerman (2009), "The Informational Role of Bond Analysts." *Journal of Accounting Research*, 47, 1201–1248.

De Long, J. Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann (1990), "Noise Trader Risk in Financial Markets." *Journal of Political Economy*, 96, 265–99.

Dechow, Patricia, Weili Ge, and Catherine Schrand (2010), "Understanding earnings quality: A review of the proxies, their determinants and their consequences." *Journal of Accounting and Economics*, 50, 344–401.

Diamond, Douglas W. (1984), "Financial Intermediation and Delegated Monitoring." *The Review of Economic Studies*, 51, 393.

Dou, Yiwei (2018), "The Debt-Contracting Value of Accounting Numbers, Renegotiation, and Investment Efficiency." *Management Science (forthcoming)*.

Dow, James and Gary Gorton (1997), "Stock Market Efficiency and Economic Efficiency: Is There a Connection?" *The Journal of Finance*, 52, 1087.

Duffie, Darrell and David Lando (2001), "Term Structures of Credit Spreads with Incomplete Accounting Information." *Econometrica*, 69, 633–664.

Edmans, Alex, Itay Goldstein, and Wei Jiang (2012), "The Real Effects of Financial Markets: The Impact of Prices on Takeovers." *Journal of Finance*, 67, 933–972.

Fama, Eugene F. (1985), "What's different about banks?" *Journal of Monetary Economics*, 15, 29–39.

Fama, Eugene F. and Kenneth R. French (2008), "Dissecting Anomalies." *Journal of Finance*, 63, 1653–1679.

Fama, Eugene F. and R. French, Ken (1992), "The Cross-Section of Expected Stock Returns." *Journal of Finance*.

Fama, Eugene F. and James D. MacBeth (1973), "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, 81, 607–636.

Franzen, Laurel, Kimberly Cornaggia, and Timothy Simin (2006), "Measuring Distress Risk: The Effect of R&D Intensity." *Journal of Finance*, 62, 2331–2368.

Gârleanu, Nicolae and Lasse Heje Pedersen (2011), "Margin-based asset pricing and deviations from the law of one price." *Review of Financial Studies*, 24, 1980–2022.

Gârleanu, Nicolae, Lasse Heje Pedersen, and Allen M Poteshman (2009), "Demand-Based Option Pricing." *Review of Financial Studies*, 22, 4259–4299.

Givoly, Dan, Carla Hayn, and Sharon Katz (2017), "The changing relevance of accounting information to debt holders over time." *Review of Accounting Studies*, 22, 64–108.

Grahman, Benjamin and David Dodd (1934), *Security Analysis: Principles and Techniques*, 1 edition. McGraw-Hill, New York and London.

Grossman, Sanford J. and Joesph E. Stiglitz (1980), "On the Impossibility of Informationally Efficient Markets." *American Economic Review*.

Hart, Oliver (2016), "Incomplete Contracts and Control." In *Nobel Prize Lecture*, 1983.

Hart, Oliver and John Moore (1994), "A Theory of Debt Based on the Inalienability of Human Capital." *Quarterly Journal of Economics*, 109, 841–879.

Hart, Oliver and John Moore (1998), "Default and Renegotiation." *Quarterly Journal of Economics*, 113, 59–96.

Harvey, Campbell R., Yan Liu, and Heqing Zhu (2016), "âŃŕ and the Cross-Section of Expected Returns." *Review of Financial Studies*, 29, 5–68.

Hayek, F. A. (1945), "The Use of Knowledge in Society." *American Economic Review*, 35, 519–530.

Hlavac, Marek (2018), "stargazer: Well-Formatted Regression and Summary Statistics Tables." URL https://cran.r-project.org/package=stargazer.

Holmstrom, Bengt (1979), "Moral Hazard and Observability." *The Bell Journal of Economics*, 10, 74–91.

Holmstrom, Bengt and Jean Tirole (1997), "Financial Intermediation, Loanable Funds, and the Real Sector." *The Quarterly Journal of Economics*, 112, 663–691.

Ivashina, Victoria and Zheng Sun (2011), "Institutional stock trading on loan market information." *Journal of Financial Economics*, 100, 284–303.

Jegadeesh, Narasimhan and Sheridan Titman (1993), "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, 48, 65–91.

Kahneman, Daniel (1973), *Attention and Effort*, volume 14. Prentice-Hall, Englewood Cliffs, NJ.

Kumar, Alok and Charles M. C. Lee (2006), "Retail Investor Sentiment and Return Comovements." *Journal of Finance*, 61, 2451–2486.

Lee, Charles M. C. and Eric C. So (2015), "Alphanomics: The Informational Underpinnings of Market Efficiency." *Foundations and Trends in Accounting*, 9, 59–258.

Ljungqvist, Alexander and Wenlan Qian (2016), "How constraining are limits to arbitrage?" *Review of Financial Studies*, 29, 1975–2028.

Lo, Alvis K. (2014), "Do Declines in Bank Health Affect Borrowers' Voluntary Disclosures? Evidence from International Propagation of Banking Shocks." *Journal of Accounting Research*, 52, 541–582.

Massoud, Nadia, Debarshi Nandy, Anthony Saunders, and Keke Song (2011), "Do hedge funds trade on private information? Evidence from syndicated lending and short-selling." *Journal of Financial Economics*, 99, 477–499.

Mayew, William J, Mani Sethuraman, and Mohan Venkatachalam (2015), "Disclosure and the Firm's Ability to Continue as a Going Concern." *The Accounting Review*, 90, 1621–1651.

Merton, Robert C. (1974), "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*, 29, 449–470.

Mitchell, Mark, Todd Pulvino, and Erik Stafford (2002), "Limited Arbitrage in Equity Markets." *Journal of Finance*, 57, 551–584.

Morck, Randall, Andrei Shleifer, and Robert W. Vishny (1990), "The Stock Market and Investment: Is the Market a Sideshow?" *Brookings Papers on Economic Activity*, 2, 157–216.

Murfin, Justin and Ryan Pratt (2019), "Comparables Pricing." *Review of Financial Studies*, 32, 688–737.

Noh, Suzie, Joseph P Weber, and Eric C. So (2019), "Voluntary and Mandatory Disclosures: Do Managers View Them as Substitutes?"

Novy-Marx, Robert (2013), "The other side of value: The gross profitability premium." *Journal of Financial Economics*, 108, 1–28.

Odders-White, Elizabeth R and Mark J Ready (2006), "Credit Ratings and Stock Liquidity." *Review of Financial Studies*, 19, 119–157.

Piotroski, Joseph D (2000), "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers." *Journal of Accounting Research*, 38.

Piotroski, Joseph D and Eric C. So (2012), "Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach." *Review of Financial Studies*, 25, 2841–2875.

Rajan, Raghuram G (1992), "Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt." *Journal of Finance*, 47, 1367–1400.

Rashes, Michael S. (2001), "Massively confused investors making conspicuously ignorant choices (MCI-MCIC)." *Journal of Finance*, 56, 1911–1927.

Shiller, Robert J. (1984), "Stock Prices and Prices Social Dynamics." *Brookings Papers on Economic Activity*, 1984, 457–510.

Shleifer, Andrei and Robert W. Vishny (1997), "The Limits of Arbitrage." *Journal of Finance*, 52, 35–55.

Shumway, Tyler (1997), "The Delisting Bias in CRSP Data." *Journal of Finance*, 52, 327–340.

Shumway, Tyler (2001), "Forecasting Bankruptcy More Accurately: A Simple Hazard Model." *The Journal of Business*, 74, 101–124.

Sloan, Richard (1996), "Do Stock Prices Fully Reflect Information in Dividends About Future Earnings?" *The Accounting Review*, 71, 289–315.

S&P Global Market Intelligence (2006), "Corporate ratings criteria." Technical report, Standard and Poor's, New York, NY.

S&P Global Market Intelligence (2018), "LCD Loan Primer - Syndicated Loans: The Market and the Mechanics." Technical report.

S&P Global Market Intelligence (2019), "Corporate Methodology: Ratios And Adjustments." Technical report, URL https://www.standardandpoors.com/en_US/web/guest/article/-/view/sourceId/10906146.

Townsend, Robert M. (1979), "Optimal contracts and competitive markets with costly state verification." *Journal of Economic Theory*.

Verrecchia, Robert E. (1983), "Discretionary disclosure." *Journal of Accounting and Economics*.

Verrecchia, Robert E. and Joseph Weber (2006), "Redacted disclosure." *Journal of Accounting Research*, 44, 791–814.

White, Halbert (1980), "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica*, 48, 817–838.

Williams, John Burr (1938), *Theory of Investment Value.*

Williamson, Oliver E (1979), "Transaction-Cost Economics: The Governance of Contractual Relations." *Journal of Law and Economics*, 22, 233–261.

Yu, Fan (2005), "Accounting transparency and the term structure of credit spreads." *Journal of Financial Economics*, 75, 53–84.