SCHOOL OF ECONOMICS AND MANAGEMENT

Does investor diversity in loan syndications affect the initial returns in the secondary market?

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Abstract

The syndicated loan market is a major source of corporate funding, raising $5 trillion in 2021. The secondary market where these loans are traded has seen a rapid growth in the last few decades. This growth was accompanied by the entrance of new types of participants, increasing the investor diversity. Similar to other markets, there is a price difference between the initial stage and the entrance in the open market. This under-pricing has been well researched in the IPO market but this research is yet to be done on these types of loans. This study investigates the impact of investor diversity on the discount. The relationship is expected to be negatively correlated, this hypothesis is reached though a theoretical argument, connecting investor diversity to market efficiency. The hypothesis was tested using historical data from the LPC DealScan database, using investor types and ownership concentration as proxies to diversity. This investigation showed statistically significant results, suggesting that the expected relationship exists. The results are robust even when controlling for fixed effects.

Keywords: Syndicated loans, Information diversity, Investor diversity, Under-pricing, Initial returns, Discount.

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1. Introduction

Syndicated loans, through which $5 trillion were raised in 2021 (*Global Syndicated Loans Review First Half 2022*, 2022), are actively traded on a secondary market. The secondary market for these loans has seen a rapid increase in trading volume in the past few decades, going from $8 billion in 1991 to $743 billion in 2019. Despite its size and increasing importance to the financial systems, the area of research studying these loans is relatively underdeveloped.

When the loans reach the secondary market, the price tends to be higher than what the lenders initially paid (Hillebrand, Mravlak and Schwendner, 2021). The drivers of this under-pricing have not previously been studied in the syndicated loan market. On the other hand, this field has been extensively studied in other areas, such as the Initial Public Offering (IPO) market, suggesting that initial under-pricing is an important aspect of understanding markets. More research on what drives the under-pricing would benefit borrowers, since the difference between the amount they raise through the issuance of the loan and the amount it is worth in an efficiently priced market could be seen as a market inefficiency that they have to pay for. The question should also interest regulators, who should want to understand the conditions allowing an efficient initial pricing of loans, enabling more fair lending conditions. The studies in information diversity which link it to market efficiency (Goldstein and Yang, 2015) provides a theoretical driver for the observed under-pricing.

The aim of this paper is therefore to study the impact that investor diversity might have in the initial discount of the syndicated loans. To answer this question, historical data of syndicated loans from the LPC DealScan database were used, the data includes both the price in the origination stage and prices in the secondary market, allowing us to calculate the initial under-pricing. The number of different investor types and the ownership concentration of these investor types were used as proxies to measure the investor diversity. A significant relation between investor diversity and the initial discount was found, concluding that additional investor diversity is contributing to an initial price closer to the price of the first day's trading.

The next parts of the paper are organized as follows. Section 2 provides background and theory of syndicated loans and the primary and secondary market. It also presents investor diversity and builds the argument resulting in the hypothesis tested in this paper. It concludes with previous studies in these fields. Section 3 describes the data used in the study and the methodology to test the hypothesis. In Section 4 the empirical results for the main study are presented and other controls performed. Lastly, in section 5, the conclusion of the study, possible improvements and future studies are presented.

2. Theory

This section gives an overview of what syndicated loans are and the basic dynamics of the primary (origination stage) and secondary (trading stage) markets. The theory section then expands on the effect of investor and information diversity in a market and the impacts it has on the market's efficiency. After connecting these two areas, the theory is synthesised in the hypothesis that will be tested to answer the research question of the paper. The section concludes with an overview of previous studies related to the topic.

2.1 Syndicated loans

A syndicated loan is a financial instrument offered by a group of lenders and is, together with corporate bonds, the largest source of public financing for corporations (Altunbaş and Kara, 2009). Syndicated loans are used by large corporations when the amount they wish to borrow is too high for a single lender to take on. Purposes for the funding raised with syndicated loans include Mergers and Acquisitions, IPO expenses, refinancing of debt, recapitalization, leverage buyout, and other.

There are different theories for why lenders want to share their exposure to a syndicated loan, instead of owning all the debt on their own balance sheet. One theory is called the *risk-exposure-diversification rationale* (Chala, 2018), where the lender joins many syndicates to diversify their loan portfolio instead of participating in fewer but bigger loans (Wilson, 1968, Schure, Scoones and Gu, 2005, Simons, 1993). Reasons for this is for example if internal control procedures do not allow the lender to buy an otherwise attractive loan due to its size (Chala, 2018).

Another theoretical explanation for why lenders sometimes collaborate in a syndicate is the *capital-adequacy-requirement rationale* (Chala, 2018). Sometimes the loan is too big to allow a single lender to contribute all the required capital, either due to liquidity concerns or capital reserve requirements.

Finally, syndicated loans could be a result of a *specialization rationale* (Chala, 2018). Large loans involve complex contracts and might require a joint monitorization between lenders in terms of the collateral and covenants agreed. Syndication allows different lenders with the necessary expertise to join larger loans, to share their different skills and competencies in terms of their controlling functions (Benston, 1994, Goldstein and Yang, 2015 and Santos, 1998). François and Missonier-Piera (2007) studied the impact of the addition of co-agents in the syndication to help the management of the syndication and to reduce the information asymmetries between lead arranger and the other syndicate participants.

Syndicated loans also enable investors to operate in regions and markets that they would otherwise not be able to access and allow smaller banks to participate in loans with large corporations, that they couldn't reach alone because of the limits of banking exposure (Simons, 1993).

2.2 Syndicated loan markets

The syndicated loan market is divided into a primary and secondary part. The primary market is the origination stage and takes place between syndicate members and the loan arranger. Since the syndicated loan shares are transferable, similarly to a bond or a share, there also exists a secondary market where these shares are bought and sold.

2.2.1 Primary market

The syndicated loan market originated loans in the primary market to a sum of $4.6 trillion in 2019 (Global Syndicated Loans Review Full Year 2020, 2020). The pandemic impacted the market, reducing syndicated lending worldwide by 24% in 2020 (ibid.). The market recovered fast in 2021 but has since reduced in size, falling 19% in the first three quarters of 2022 as investors shifted to a more risk averse approach (*US syndicated loan volume down 15% in 2022 amid bearish sentiment*, 2022).

Commercial banks are often the arrangers of syndicated loans, but the syndicate members that take part in the primary market include commercial and investment banks, insurance companies, mutual funds, and other institutional investors (Dennis, 2000).

Since 2010, the top two bookrunner of syndicated loans by amount were BofA Securities Inc and JP Morgan. The corporations that use this type of financing mainly operate in the energy and power, financial, and industrial sectors (Global Syndicated Loans Review Full Year 2020, 2020).

The syndication process begins with the selection of the lead arranger by the borrower. The syndication leader is responsible for the pricing process, including interest rate charged and the associated fees. The selection of the leader is based on different aspects such as the proposed terms and conditions of the facility (fees, commitment covenants or others), the share of the loan the lead is willing to retain, previous relationship and the reputation and experience of the lender as a syndicate leader (Taylor and Sansone, 2009). If more than one prospective investor is interested in the leading role, the final selection might be decided through a competitive bidding process, where the borrower will compare the proposals of each one and choose the one with the most favourable terms as lead arranger (Chala, 2018).

In this phase of the syndication other key structural parts of the contract, such as covenants, tenor, total amount and other fees are also settled. The syndicated process includes a lot of different fees over time, to the arranger but also to the other syndicate members. The fees paid can have a significant impact in the borrowers total cost of lending, sometimes even being more important than the agreed margin (Allen, 1990, Berg, Saunders and Steffen, 2016).

When the leader has been chosen by the borrower, the terms and conditions of the contract are negotiated directly between the two parties (Chala, 2018). The lead arranger can choose to *fully underwrite* the amount of the syndicated loan or undertake the syndication in a *best-effort basis*. In the first case, the leader takes the risk of finding enough interested investors to cover the loan or keep the remaining part in their own books. The best-effort method keeps the risk of not finding enough participant to join the syndication in the borrower side, without any responsibility for the lead to undertake the non-allocated parts of the loan (Chala, 2018).

The terms agreed are summarized in a term sheet that will be presented to the participants of the syndication. There will be a single loan agreement contract with the same conditions for all the lenders that accept to join the syndicated loan (Gadanecz, 2004).

The pricing process takes the credit quality of the borrower, market conditions, comparable prior transactions and similar loans in the market, the relation between borrower and lender, secondary market trends and the overall valuation of the borrower into consideration (Taylor and Sansone, 2009).

Syndicate shares are allocated though a sealed-bid auction system, similar to a book-building in an IPO, where the interested borrowers submit proposals of the amount they are willing to lend and at which rate (Grupp, 2015). If the arranger finds that the demand for the loan on the terms offered is higher than expected, that the loan is over-subscribed, the arranger can scale allocations to the interested lenders (Godlewski and Weill, 2008). Thus, this process is susceptible to similar oversubscription issues as IPOs (Ritter and Welch, 2002), where the demand for an asset at a specific price is higher than the supply, resulting in a price increase as soon as the asset hits the secondary market.

Apart from the initial returns observed due to higher demand that cause an increase in the price on its first days of trading, there might also exist a discount in the initial price of the loan in term to its par value, original issue discount. This discount in the initial price may have different reasons, such as increased risks associated with the borrower, a lack of publicly available information on the borrower and the borrower credit rating. Characteristics of the loan structure may also play a role in the original issue discount such as loan seniority, whether covenants exist or if the loan is secured. Market wide macroeconomic trends and events, such as the interest rates or growth outlooks, are other factors that may impact the Original Issue Discount.

2.2.2 Secondary market

The secondary loan market trading volume has grown from $8 billion in 1991 to $743 billion in 2019 according to the Loan Syndicated Trading Association (Santos and Shao, 2022). This is a compounded annual growth rate of 28,5%. Despite the size of the market, it remains largely self-regulated (Saunders, Shao and Xiao, 2022).

Traditionally, only banks participated in these markets, often holding the loans to maturity (Bord and Santos, 2012). In recent decades, other types of actors have entered the market, and these types of loans are now traded in an active market (Bord and Santos, 2012), between a much more diverse pool of investors. These investor types include insurance companies, hedge funds, investment banks and other financial institutions.

The last two decades has seen a rapid increase in the diversity of the institutional investors participating the syndicated loan markets. Irani *et al.*, (2021) found that non-bank funding increased from about 20% in 1993 to 70% in 2014. Lee et al (2019) argues that the market has become more reliant on an originate-to-distribute model (OTD), as opposed to an originate-to-hold model to supply this increased demand. The OTD model brings with it certain risks, one of these mentioned by Lee *et al.*, (2019) is the *pipeline risk*, where a sudden decrease in demand makes loans already in the *pipeline* harder to distribute, forcing banks to retain a large share of these loans on their balance sheet.

Oversubscription in the origination stage, as described in the previous section, can cause a price difference between the primary and secondary markets. Hillebrand, Mravlak and Schwendner (2021) shows that the prices, or yields, discovered in the two different markets tend to be different, with higher yields in the primary market compared to the secondary market. This yield difference, or under-pricing, means that it is cheaper to participate in the syndicated loan at origination than it would be to buy the same loan share in the secondary market.

2.3 Investor Diversity

The basic definition of market efficiency depends on the amount of information contained in the pricing of assets in capital markets (Fama, 1970). It should therefore follow that additional information available in a market increases its efficiency. Figlewski (1982) argues that investors may have access to different pieces of relevant private information that is not widely available. The paper shows that market participants with *any* additional information the market has not yet discounted is able to make a theoretical profit. The trading on this additional information then incorporates it into the market price, increasing market efficiency. Goldstein and Yang (2015) continues the same trend, they show that different types of investors have been shown to produce different kinds of information, improving market efficiency though actors aggressive trading on their proprietary information. Similarly, Wei (2017) find a connection between belief diversity and price informativeness, linking it to market efficiency.

Goldstein and Yang (2015) argue that the diversity of information decreases the uncertainty of the accuracy of the price and thus encourages additional trading. Santos and Shao (2022) empirically test the impact of investor diversity on liquidity in the secondary syndicated loan market and find results compatible with this theory.

2.4 Hypothesis building

Comparing the market efficiency of the two syndicated loan markets, the primary market is less efficient than the secondary market due to the differences in market frictions. The secondary market is a comparatively open marketplace where any institutional investor can buy and sell their loan shares to a relatively efficient price. In the primary market, on the other hand, relatively few investors are invited to participate in the loan origination, resulting in a less efficient price discovery. For the reasons mentioned in the section about investor diversity, there should be a positive correlation between investor diversity and market efficiency. Therefore, an increase in the investor diversity in the origination stage should increase market efficiency and reduce the distance between the price at origination and the price in the secondary market.

This paper explores the effect of investor diversity on the under-pricing of syndicated loans, using similar methods to the ones used by Santos and Shao (2022). The returns on the first day of trading are measured as the difference between the first quotation price and the original issue discount. Investor diversity is measured by the number of different types of investors participating in the loan origination and the concentration of loan share ownership for different investor types.

Following from the above theoretical arguments, the hypothesis of this paper is that investor diversity in the primary syndicated loan market is negatively correlated with the discount between first day trading and origination prices.

2.5 Previous Studies

The study of under-pricing in the syndicated loan market is analogous to the study of under-pricing in the area of initial public offerings (IPO). Logue (1973) and Ibbotson (1975) were some of the earliest studies of stock under-pricing, measuring statistically significant returns when the price offered in the IPO were compared to the price in the first days of trading. In the following years there were some studies of the average under-pricing, finding on average 12% returns in the 1970s and reached almost 40% in the first four years of 2000s (Ljungqvist, 2007). The IPO discount observed was also found to be dependent on where the firms went public. For example Poland showed an IPO under-pricing mean of almost 60% between 1990 and 2003 while the same measurement for Luxembourg and Denmark was below 10% for the same period (Ljungqvist, 2007). Asymmetric information, institutional reasons, control considerations, and behavioural approaches have been identified as reasons for IPO under-pricing (Ljungqvist, 2007).

While not as popular of a research topic as the stock market, the fast growth of the syndicated loans and its secondary market has drawn the attention of some researchers over the last years. The studies have mainly been focused on the way the market operate, its liquidity, reasons for its growth and the entry of new types of investors.

Santos and Shao (2022) found that syndicated loans with higher initial ownership diversity, measured by the number and concentration of investor types, have higher liquidity in the secondary market. They considered that different types of investors take different information in consideration when valuing a company. The complementarities on these different approaches give more incentives to trade in the market and increase the confidence of investors to buy shares of the loans. This aggressive trading on the produced information decreases uncertainty and encourages trading, increasing their liquidity (Goldstein and Yang, 2015).

Blickle *et al.* (2020) studied the effect on the quality of syndicated loans when the lead arranger sells their initial share. Their paper is called "The myth of the lead arranger's share", because they find results that contradicts some classic theories that relate the retention of the lead arranger's share in the loan and the information asymmetry problem.

One of the classic theories is adverse selection. The originator banks are assumed to have more access to private information than other syndicated loan participants. With the private information they are theoretically able to select loans with higher quality to keep on their balance sheet and sell the loans of lower quality. The fact that the originator retains their share in the syndication could therefore be a signal of higher quality loans (Leland and Pyle, 1977).

Moral hazard, another classic theory, argues that if banks have no risk exposure to the borrower, they have less incentive to monitor and screen borrowers, as these activities are associated with significant costs. This may reduce the quality of their risk analysis and increase the risk to uninformed investors in the market with exposure to that borrower (Gorton and Pennacchi, 1995). Gorton and Pennacchi (1995) and Holmstrom and Tirole (1997) found that if the arranger retains a significant large portion of the loan, it will have incentives to make sufficient efforts in its monitoring and screening responsibility, overcoming the moral hazard problem for the rest of the investors.

Blickle *et al.*, (2020) formulated three hypotheses conformant with the adverse selection and moral hazard theories. The hypotheses stated that (1) the lead arranger rarely sell their share immediately after the origination; (2) the lead arranger is less likely to sell their share compared to other participants and (3) loans that are sold by the arranger immediately after the origination, tend to perform worse in the future. Contrary to what was expected according to the theories presented above inconsistent results were found to the three hypotheses. The reason for this could be that the information asymmetries were overestimated, since the syndicated loan market is comprised of institutional investors, such as collateralized loan obligations (CLOs) vehicles, that perform their own analysis and due diligence on each borrower (Blickle *et al.*, 2020). Another explanation is that the arranger has other incentives to monitor the borrower, such as commitment to underwrite and reputational risks.

The findings of Blickle *et al.* (2020) show that the retention by the arranging bank is not as important in the syndicated loan market as it is in the mortgage market, where previous studies showed that mortgages with higher retention by the originator perform better in the future (Begley and Purnanandam, 2017).

In an underwriting deal, the arranger guarantees to the borrower the terms and the amount of the loan, often bearing the demand risk. If the amount raised in the market is less than the amount negotiated with the borrower, the arranger may have to fund the difference (Bruche and Malherbe, 2019). This study also concludes that the retention share of the arranger is larger when the loan is cold (lower demand), reflecting pipeline risk. This reason for retained share contrasts with others presented above, such as adverse selection, where the retention was used to signal the market of the quality of the loan.

3. Data and methodology

This section presents the data sources used in the study (Section 3.1), the combination and filtration of the data sets (Section 3.2) and the methodology used to answer the research question (Section 3.3).

3.1 Data

Historical data of the syndicated loan markets were gathered from the Refinitiv Loan Pricing Corporation (LPC) DealScan datasets. Capital IQ was used to classify the lenders as different investor types. The linking of investors between the two data sources were aided with the help of a matching table used earlier by the authors of Forssbaeck *et al.* (2023).

3.1.1 Historical loan data

Refinitiv LPC DealScan ("LPC DealScan") is a global provider for syndicated loan, direct lending, and CLO market data and is the most used data source in the topic of syndicated loans. The information is collected from filings to the Security Exchange Commission (SEC) by borrowers, arrangers and other syndicate members, as well as other public sources. The collection of data started in the early 1990s and includes data from as early as 1981. The data gathered from LPC DealScan is divided into two data sets, depending on whether it pertains to the primary or secondary syndicated loan markets.

3.1.1.1 Primary market

The primary data set describes syndicated loan originations. The primary data used in this study begins in 1987 and ends in 2020. The data is organized into deals, where each deal is connected to one specific borrower. The deals are then divided into tranches which, in turn, are sometimes amended after the tranche is initially activated. In this paper each tranche activation is treated as a separate observation, a tranche activation is defined as both the initial activation and all amendments afterwards. The characteristics of each tranche can vary throughout the different activations, most importantly for this paper is the fact that the syndicate members participating in each tranche activation often changes which means that the investor diversity make up of the loan also may change. In Table 1, the total number of deals, tranches and tranches activations in the primary data is presented. Each tranche had an average of 1.62 activations and each tranche activation has around 8 syndicate lenders on average.

Each tranche activation is described in detail, the data set includes information about the borrower, the syndicate members and the loan characteristics. The borrower information includes name, parent name (when applicable), location, industry, loan purpose, borrower credit rating and others. The syndicate members are described by name, location, lender credit rating and other data points such as the loan share allocated to each lender. The deal information includes total deal and tranche amount, both in original currency and in USD. It also includes the deal type, maturity in months, activation and maturity date, seniority, spread, margin and details on financial covenants when applicable.

Critically, some loans also include information of the price paid, in terms of par value, for the loan. This data point is called the Original Issue Discount (OID) and is later used to calculate the under-pricing, or discount, when compared to the quoted prices in the secondary data set. The tranches are assigned a Loan Identification Number (LIN) that is used to identify them in the secondary market. Since this matching between the data sets is needed to perform the study, the primary data set was filtered to only include tranches with a LIN. As a result of this, only tranche activations in 2000 and later are included in the study.

Table 1 - Information Primary Data

Total number of Deals	14,806
Total number of Tranches	26,561
Total number of Tranche Activations	43,078
Average number of Activations per Tranche	1.62
Total number of Tranche Activation Lenders	342,440
Average number of lenders per tranche activation	7.95
Average Deal Amount (m USD)	1,111.28
Average Tranche Activation Amount (m USD)	568.41

Table 1: Descriptive statistics of the primary syndicated loan market gathered from Refinitiv LPC DealScan. Tranche activations are defined as either the initial activation or an amendment to a loan tranche. The data includes all tranche activations between 2000 and 2020 with a loan identification number.

The temporal distribution of the number of tranche activations and deals are presented in Figure 1 and 2. The significant drop of both tranche activations and deals in 2008 and 2009 is presumably due to the great financial crisis, interestingly, the return to normal deal activity was relatively quick.

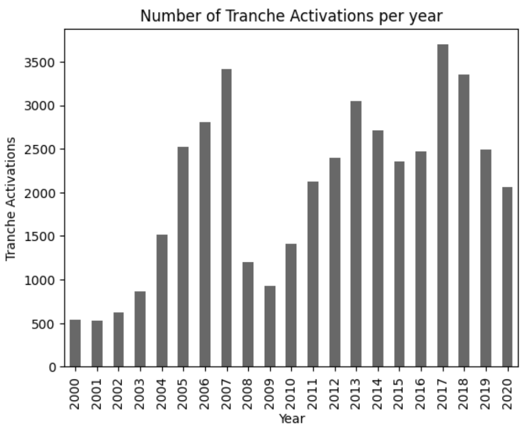

Figure 1 - Number of Tranche Activations per year

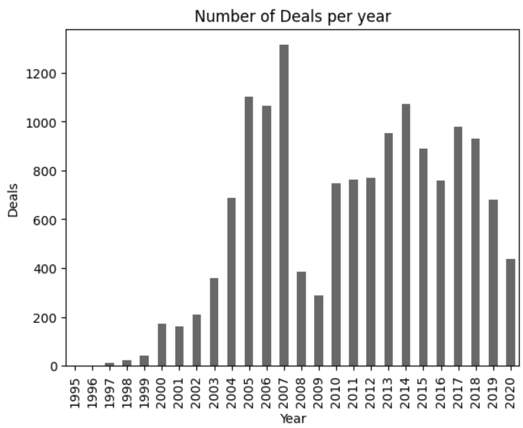

Figure 2 - Number of Deals per year

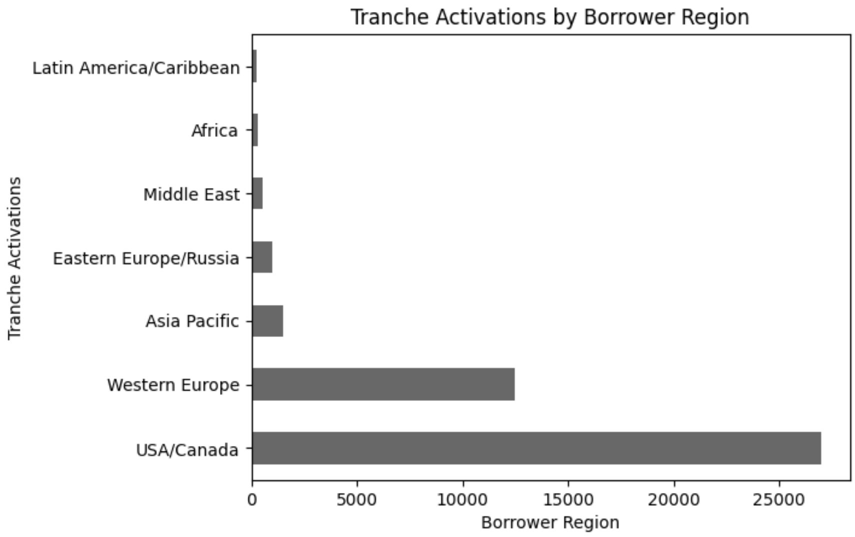

Figure 3 - Tranche Activation by Borrower Region

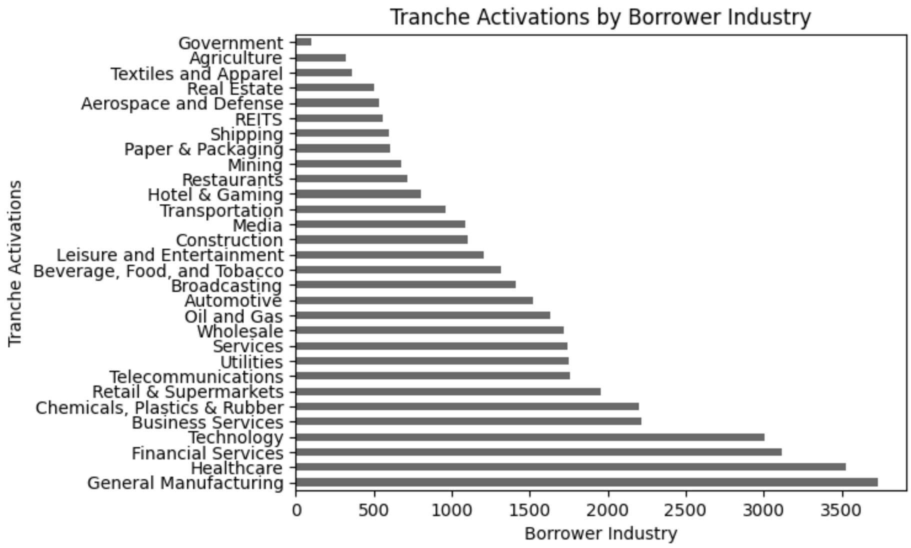

Figure 4 - Tranche Activations by Borrower Industry

The geographical region and main industry of operations of the borrowers are visualised in figure 3 and 4, respectively. From these figures it is clear that the syndicated loan market data is primarily populated by borrowers from USA/Canada and Western Europe and that they mostly operate in manufacturing, healthcare, financial services and technology.

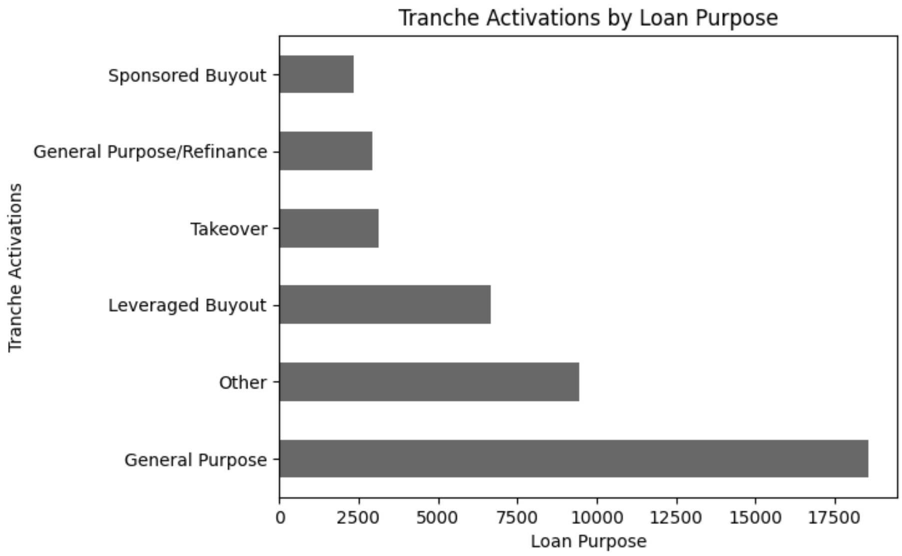

Figure 5 - Tranche Activations by Loan Purpose

The syndicated loans have diverse purposes, as shown in figure 5, with general and other including the most observations. The most often cited, more specific, loan purpose all seem to refer to some kind of M&A activity.

3.1.1.2 Secondary market

The data set for the secondary market is organized by tranche, identified by a Loan Identification Number (LIN), and the date the quoted price was given. The LIN is also available for the tranches in the primary data, which enables the matching between the two data sets. For each LIN and date combination the average quoted bid and ask prices are reported. The middle point between the bid and ask price is called the Mean of Mean and is considered to be the market price of the instrument at that given day. Additional information is also included in the data set, such as number of quotes that day and the signing date of the tranche, as well as the maturity, spread, currency, country, and borrower industry. Price quotations are reported daily. The data used in this study is from 2002 to the third quarter of 2020.

The quoted prices are reported in terms of par value, without any information of the actual traded value. Since both the quoted prices and the original issue discount at origination are reported in the same units they are comparable between both the primary and secondary data sets.

The total number of quotations observed in the secondary market data and the number of different LINs are presented in table 2. This table also shows the average number of observed quotes per LIN, around 500, meaning that, on average, each LIN was quoted for 1.5 years. In reality these quotes are often not continuous periods and some LINs are quoted for longer periods than others.

Table 2 - Information Secondary Market

Total number of Quotes	20,276,041
Number of different LINs	37,411
Average number of quotes per LIN	541.98
Average quoted Mean of Mean	92.77

The number of quotes per year is presented in figure 6. The secondary market activity rapidly increased between 2002 and 2007, when it peaked. In the past years, the number of quotes has been declining. Since the data set only includes data up to the third quarter of 2020, the decline in number of observed quotes visible in the figure might not represent a real reduction in market activity when compared to the previous year.

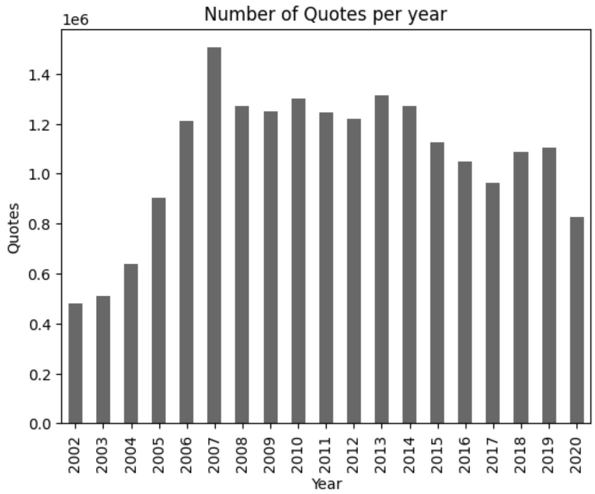

Figure 6 - Number of Quotes per year

3.1.2 Lenders data

To measure the investor diversity the data from LPC DealScan needed to be appended with additional information about the lender. To accomplish this the lenders industries were gathered from Capital IQ.

Capital IQ was founded in 1999 and is one of the world's largest providers of information of the financial markets. Every year they collect and report information from public and private companies, claiming to cover 99% of all the public companies worldwide.

The lenders were found in the Capital IQ database through a multiple step process where first the lender names were searched, and if no match was found the name of the lenders parent company was searched. If no match was found by searching the two names a matching table provided by our supervisor was used. The table had been created earlier for use in Forssbaeck *et al.* (2023) and had matched many lenders in the database with their corresponding ID in Capital IQ.

When the lenders had been found in Capital IQ the Global Industry Classification Standard (GICS) code was used to separate them into different investor types. If the company identified in

Capital IQ was classified as a non-financial company (i.e. a Global Industry Classification Standard (GICS) code not starting with 40), the lender was classified as “Other”, since all investors participating in the syndicated loan market should be institutional investors. The primary data set has 5.563 unique lenders and the industry was identified for 86% of them. The remaining 14% was classified as “Other” industries.

In figure 7, the number of tranche activations per type of lender is presented.

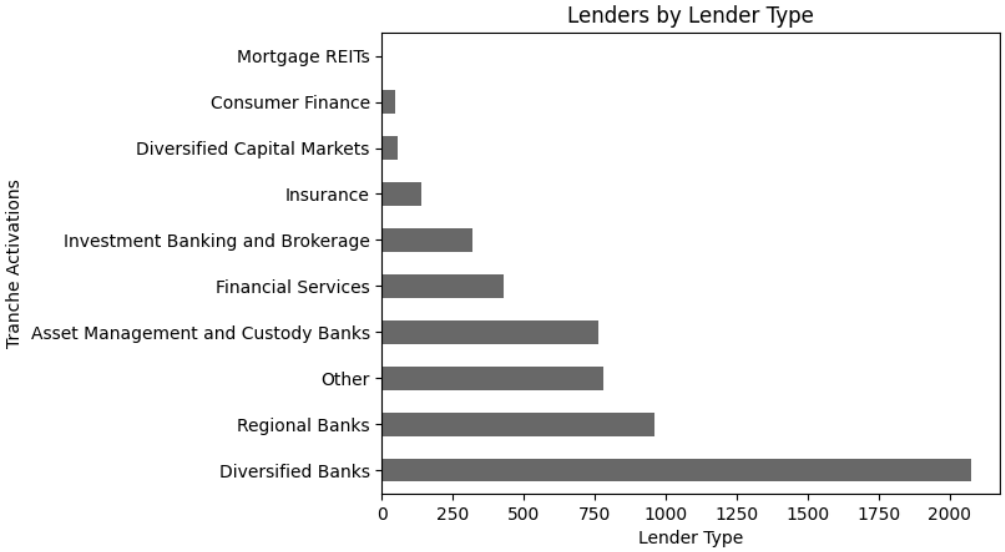

Figure 7 - Lenders by Lender Type

3.2 Combined data and Sample characterization

Lastly, these three data sources were combined to a final data set. The matching of lenders with the capital IQ dataset is described above. The matching was done by finding the first quote after the tranche activation date for each tranche activation using the LIN of each tranche. After this matching, the combined data set was organized by tranche activations and contained information from all three data sets, allowing us to compare the Original Issue Discount (OID) from the primary data, first quoted price (Mean of Mean) from the secondary data and lender types from Capital IQ.

The dependant variable tested in this paper is the discount between the price quotation in the first observed trading day and the initial price the syndicate members paid for the loan. The discount of the loan, $DISCOUNT_i$, was estimated using the Original Issue Discount, OID, and the mean quoted bid and ask prices from the first observed quotation, $Mean\ of\ Mean$.

$$DISCOUNT_i = Mean\ of\ Mean_{i,t=1} - OID_i \ , \quad (1)$$

For tranches where no OID is available in the data, the mean of the available OID values (99.026) were used. This is motivated by the relatively low standard deviation between the different observations, around 1.47, which would suggest that the mean would on average be a good estimate of OID on other observations. The impact of this decision is later explored in section 4.5.

For the purpose of the paper, the discount observed between the first quotation price and the OID, represents the initial returns. In the final sample, only tranches where a price was quoted within the first 30 days of tranche activation were included. This filtration was performed to isolate the initial returns the paper is interested in from price changes that can happen later in the loan's lifetime. It is not uncommon for a tranche to be quoted the first-time years after the loan was originated, if these price observations from the secondary market were included, additional information, not available at the origination stage, would disturb the signal this paper seeks to study.

The effect of the filtrations on the sample is shown in table 3 and shows that the size of the data set was reduced to about 5% of its original size. The biggest reduction was observed when the filtration to only include observations with an identification number was performed. The reason for why the LIN is missing for these observations is thought to be that the loans either were not quoted in the secondary market or that any quotation for some reason was not recorded in the DealScan database. It seems safe to assume that even though the trading volume of these loans have increased, most loans remain held on the lenders balance sheets until maturity.

Table 3 – Sample filtrations

Tranche Activations, Primary data	352,443
Tranche Activations with LIN	43,078
Tranche Activations with quotations	33,203
Tranche Activations quoted in the first 30 days	17,456

Table 4 - Descriptive statistics combined data.

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
DEPENDANT VARIABLE					
ORIGIAL ISSUE DISCOUNT (OID)	99.021	0.832	99.026	99.026	99.026
MEAN QUOTE	98.469	6.423	99.000	100.000	100.500
DISCOUNT	-0.552	6.389	0.099	0.750	1.375
WINSORIZED DISCOUNT	0.403	1.462	0.099	0.750	1.375
DIVERSITY					
TYPES	2.738	1.329	2.000	3.000	3.000
HHI	0.548	0.241	0.372	0.500	0.625
LOAN					
LOG AMOUNT	5.705	1.128	5.011	5.704	6.429
MATURITY	66.173	21.853	54.000	70.000	84.000
RATE	5.505	2.607	3.799	5.250	7.186
ARRANGER SHARE	64.523	36.127	33.333	66.667	100.000

Table 4: The full descriptive statistics of all the variables used in the study, including all the dummy variables are presented in section 6, table 13.

The descriptive statistics of the final sample are presented in table 4. Here, it is possible to observe that the mean quoted price has a high standard deviation of around 6.4 when compared to the OID from the primary data. This could be a result of outliers present in the secondary data. To reduce the impact of these outliers the discount was winsorized at the 10th and 90th percentile, reducing standard deviation to around 1.5. The winsorized values in $WINSORIZED\ DISCOUNT$ will be used for the remainder of this paper and is shortened to called $DISCOUNT$.

The number of different types of investors participating in the syndicated loan origination, $TYPES$, and the Herfindahl-Hirschman Index (*Herfindahl-Hirschman Index*, 2015), HHI, of the loan share ownership concentration of these types, will be used as proxies to measure investor diversity.

$$HHI_i = \sum s_{i,j}^2, \qquad s_i: 0 < s_i \leq 1, \;\; (2)$$

The ownership share of each type of investor, s_i, is measured as a percentage of the total loan amount. The ownership share for each syndicate member is often available in data set, when this information is missing for some or all lenders, the unallocated loan share was divided equally between the lenders. After this, the lenders were grouped by investor type and their ownership shares were summed. Using this methodology, the total ownership of each tranche activation is ensured to add up to 1. The maximum value of HHI is 1, corresponding to a loan only subscribed by one investor type and is subsequently the least diversified. Lower values of the index, represent more diversified loans.

As presented in the section 3.1.2. the lenders were all combined in 10 different categories, Diversified Banks, Diversified Capital Markets, Investment Banking and Brokerage, Regional Banks, Asset Management and Custody Banks, Consumer Finance, Financial Services, Insurance, Mortgage REITs and Others.

The primary data set assigns all participating investors a *primary role*, these roles were manually sorted into three categories, arrangers, syndicate participants and non-participants. For example, the entities assigned the role Legal Advisor were classified as non-participants while the Lead Bank was classified as an Arranger. The non-participants were not considered in the rest of the analysis. $ARRANGER\ SHARE$ is the percentage of the total loan amount that was allocated to lenders classified as Arrangers. Just like the ownership share of the investors, this value is between 0 and 1.

The total amount, in millions of dollars, linearized with a log-transformation, $LOG\ AMOUNT$, the tranches time to maturity in months, $MATURITY$, and rate of the loan, $RATE$, were used as controls for characteristics of the loan. The interest rate of the loans was reported as a margin and a reference rate. The $RATE$ used in the study was calculated by adding the value of the reference rate at the time of tranche activation to the margin. Out of the tranche activations with a listed reference rate, around 90% used LIBOR or EURIBOR. The values for these two reference rates were collected from Capital IQ. Other reference rates were not considered.

Some binary variables describing different loan characteristics were added to the loan-specific controls. The binary variables are 1 if true and 0 otherwise. They signalled if the loan had seniority over other loans, $SENIORITY$, if the loan was secured, $SECURED$, had covenants, $COVENANTS$, was amended, $AMENDED$, or had call protection, $CALL\ \ PROTECTION$.

There were also categorical dummy variables used in specific-loan and specific-borrower controls. Small categories with less than 100 observations in the data set were combined in a "Other" category to reduce the overfitting on these loans. When creating the dummy variables, one of the categories were always excluded to avoid the dummy variable trap (Brooks, 2008). In the rest of this paper, the excluded category for each variable is called the reference category.

The primary purpose of the loan, $PRIMARY\ PURPOSE$, had 34 different categories in the combined dataset but only 6 had more than 100 observations. The categorical variable of $PRIMARY\ \ PURPOSE$, was translated to six dummy variables $AQUISITION$, $GENERAL\ PURPOSE/REFINANCE$, $LEVERAGE\ BUYOUT$, $SPONSORED\ \ BUYOUT$, $TAKEOVER$ and $OTHER\ \ PURPOSE$. $GENERAL\ PURPOSE$, is the category with highest number of observations and is considered the reference to the other dummies.

The categorical variables used as borrower controls, treated in a similar way, were the region of the borrower, $REGION$, its main industry of operations, $INDUSTRY$, and its credit rating, $RATING$.

The borrower $REGION$ was translated to 4 dummy variables, $ASIA\ PACIFIC$, $EASTERN\ EUROPE/RUSSIA$, $WESTERN\ EUROPE$ and $OTHER\ REGION$. The reference dummy excluded in this category is $USA/CANADA$.

The categorical variable of borrower $INDUSTRY$, was translated to 14 dummy variables $Automotive$, $Beverage, Food\ and\ Tobacco$, $Business\ Services$, $Chemicals$, $Financial\ Services$, $General\ Manufacturing$, $Healthcare$, $Oil\ and\ Gas$, $Retail\ and\ Supermarkets$, $Services$, $Technology$, $Telecommunications$, $Utilities$ and $Wholesale$. The reference category excluded was $Other\ Industries$.

The borrowers credit rating from different providers were included in the primary data set. If the borrower had been rated by any rating provider, this was recorded in the binary dummy variable $RATED$. The different ratings were then condensed into one single categorical variable, this was done by finding the ratings provided by any of the three biggest rating providers, Moody's, S&P and Fitch. The credit rating received from these three providers were translated to a numerical values (AlAli, AlSabah and AlForaih, 2018). If more than one provider had given a credit rating, the mean value was used. The numerical value was then translated back into a categorical value. Similar ratings were grouped together, ratings from AAA to A were combined into one category, $AAA - A$, because these are the higher quality companies with similar and lower risk. Ratings between CCC and D were also combined into one category, $CCC - D$, these ratings are assigned to companies with a high risk of imminent default or is already in bankruptcy. Companies with triple B rating (BBB+, BBB or BBB-) were combined in the category, BBB. These companies are still classified as investment grade but with lower quality than the ones classified with an A rating. Ratings form BB+ to B-, are rated as speculative grade companies and represent higher risk but not in imminent risk of default. For these, each rating was kept as a separate category, $BB+$, BB, $BB-$, $B+$, B, and $B-$. This categorical variable, $RATING$, was translated to 9 dummy variables and the reference dummy excluded is the borrowers without rating.

The tranche activation date was used to create one dummy variable per year, to account for year fixed effects. The year with the highest number of observations, 2017 is considered the reference dummy and was therefore excluded.

3.3 Methodology

To answer if initial investor diversity has an impact on the discount of syndicated loans and to measure the magnitude of this relationship, the model for $DISCOUNT$ presented in equation (3) and (4) were used. The regression setup largely follows the same pattern as Santos and Shao, 2022).

The dependant variable in the regression is the $DISCOUNT$ defined in equation (1). The independent variables measuring the investor diversity are $TYPES$ and HHI. In addition to the investor diversity measurements the model includes the loan-specific controls, borrower-specific controls, and year fixed effects described above. The year fixed effects are included to account for time heterogeneity. The model specifications are as follows:

$$DISCOUNT_i = \alpha + \beta\, TYPES_i + \sum \delta_k Loan_{i,k} + \sum \lambda_l Borrower_{i,l} + \sum \gamma_m Year_{i,m} + \epsilon_i\,, \quad (3)$$

$$DISCOUNT_i = \alpha + \beta\, HHI_i + \sum \delta_k Loan_{i,k} + \sum \lambda_l Borrower_{i,l} + \sum \gamma_m Year_{i,m} + \epsilon_i\,, \quad (4)$$

4. Results

In this section the results of the impact investor diversity have on discount are presented, first without any additional controls (Section 4.1), then with loan controls (Section 4.2), borrower controls (Section 4.3) and year fixed effects (Section 4.4). In section 4.5 the results of the regression where these controls are combined are presented. The results section then concludes in section 4.6 presenting the results of the robustness tests and OLS assumption tests that were performed.

4.1 Relation between discount and investor diversity proxies

Figure 8 shows a boxplot of the discount for loans with different number of investor types. In this figure a negative relation of the median discount with the number of investor types can be observed. This seems to be in accordance with what was expected when developing our hypothesis for this paper. The number of observations is significantly lower for the most diverse loans which might explain the more volatile quantiles present when the number of investor types reaches more than 7.

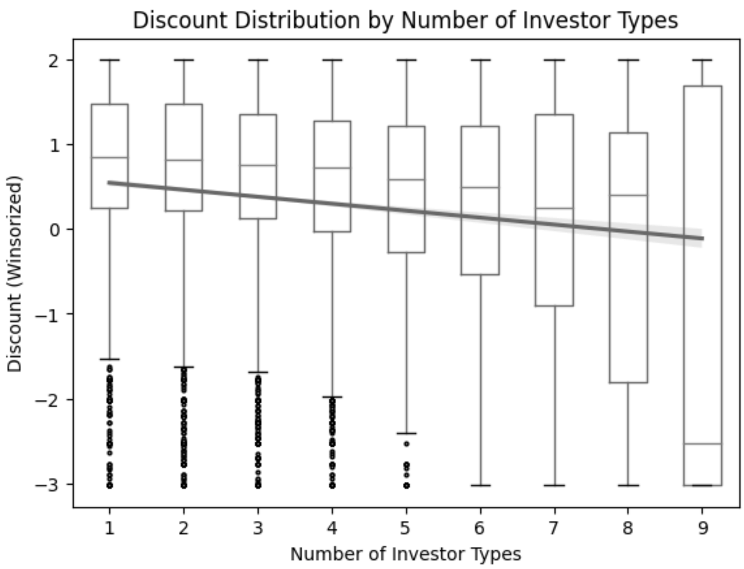

Figure 8 - Discount distribution by Number of Investor Types

In figure 8, the line is the regression line for the relationship as shown by equation (5). The regression results are presented in table 5.

$$DISCOUNT_i = \alpha + \beta\, TYPES_i + \epsilon_i\,, \quad (5)$$

Figure 9 is a density graph that have different hue for different amounts of observations in each part of the grid, with the highest density presented in the brightest area and the lowest in the darkest area. A significant part of the data has an initial discount between 0 and 2%, in relation to par value, and a concentration measured by the HHI between 0.3 and 0.6. For 2 and 3 different types of investors, with the same share of the loan for each type, the HHI would be around 0.5 and 0.333, respectively. From the figure we might conclude that a large part of the data will have around 2 or 3 different types of investors. The regression line presented in figure 9 shows a slightly positive relation between the discount and HHI, and seems to agree with our hypothesis being tested.

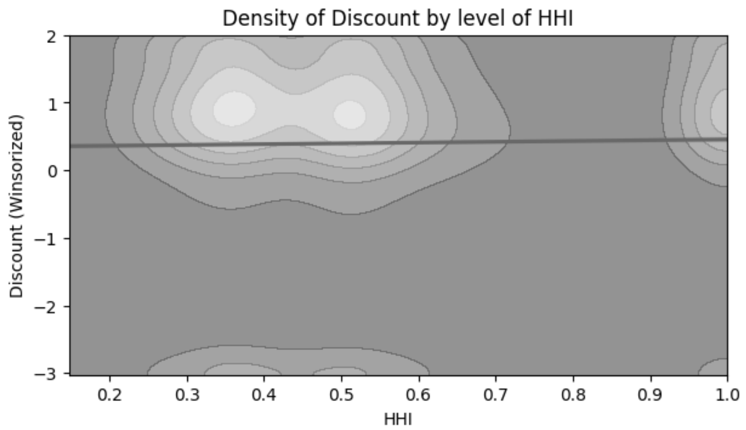

Figure 9 - Density of Discount by level of HHI

Similar to the regression for $TYPES$, the relation between the discount and the proxy for investor concentration, HHI, was tested by the model in equation (6). The results of the regression are presented in table 5.

$$DISCOUNT_i = \alpha + \beta\ HHI_i + \epsilon_i\ , \quad (6)$$

Table 5 - No controls

Variables	Coeff		t-value	Coeff		t-value
TYPES	-0.0821	***	(-8.2567)			
HHI				0.1164	**	(2.3035)
R-Squared	0.0056			0.0004		

*** 1% significance level; ** 5% significance level; * 10% significance level

The low R-squared for both regressions indicates that $TYPES$ and HHI explain only a small portion of the total variance of the discount. However, the significant relationship at a 1% significance level for $TYPES$ and at 5% significance level for HHI implies that there is evidence to support the presence of a statistically significant negative and positive relation, respectively, between the dependent and independent variables. The signs of these relationships were the ones expected by the hypothesis and confirm the linear relations presented in figure 8 and 9.

In conclusion, the diversity measurements are shown to have a statistically significant impact on the dependant variable, $DISCOUNT$, with the expected sign but the low R-squared value suggests that a large part of the variation is still unexplained.

4.2 Controlling for loan variables

To increase the explanatory power of the model, apart from the independent variables of investor diversity, $TYPES$ and HHI, loan-specific controls were included. The model is presented in equations (7) and (8), and the additional variables are explained in section 6, table 12. The results of these regressions are presented in table 6.

$$\begin{aligned} DISCOUNT_i = \alpha + \beta\, TYPES_i + \delta_1 LOG\ AMOUNT_i + \delta_2 MATURITY_i + \delta_3 RATE_i \\ + \sum \delta_{4,j} PRIMARY\ PURPOSE_{i,j} + \delta_5 SECURED_i + \delta_6 SENIORITY_i \\ + \delta_7 COVENANTS_i + \delta_8 DEAL\ AMENDEMENT_i + \delta_9 CALL\ PROTECTION_i \\ + \delta_{10} ARRANGER\ SHARE_i + \epsilon_i\,, \quad (7) \end{aligned}$$

$$\begin{aligned} DISCOUNT_i = \alpha + \beta\, HHI_i + \delta_1 LOG\ AMOUNT_i + \delta_2 MATURITY_i + \delta_3 RATE_i \\ + \sum \delta_{4,j} PRIMARY\ PURPOSE_{i,j} + \delta_5 SECURED_i + \delta_6 SENIORITY_i \\ + \delta_7 COVENANTS_i + \delta_8 DEAL\ AMENDEMENT_i + \delta_9 CALL\ PROTECTION_i \\ + \delta_{10} ARRANGER\ SHARE_i + \epsilon_i\,, \quad (8) \end{aligned}$$

Table 6 - Loan Controls

Variables	Coeff		t-value	Coeff		t-value
TYPES	-0.0241	**	(-2.4947)			
HHI				0.1144	**	(2.4484)
Loan Controls	YES			YES		
R-Squared	0.1708			0.1707		

*** 1% significance level; ** 5% significance level; * 10% significance level

From table 6, the results show that the loan variables contribute to explain a more significant part of the variation in the initial discount, with an R-squared above 17% for both regressions. The sign of the investor diversity measurements stayed the same when the loan controls were added but the significance level is now 5% for both HHI and $TYPES$.

4.3 Controlling for borrower variables

The explanatory power of the model was also tested with the borrower information available in the primary data. The regressions are presented below and the results in table 7. The variables are explained in section 6, table 12.

$$DISCOUNT_i = \alpha + \beta\, TYPES_i + \sum \lambda_{1,j} REGION_{i,j} + \sum \lambda_{2,k} INDUSTRY_{i,k}$$

$$+ \sum \lambda_{3,l} RATING_{i,l} + \lambda_4 RATED_i + \epsilon_i\ , \quad (9)$$

$$DISCOUNT_i = \alpha + \beta\, HHI_i + \sum \lambda_{1,j} REGION_{i,j} + \sum \lambda_{2,k} INDUSTRY_{i,k}$$

$$+ \sum \lambda_{3,l} RATING_{i,l} + \lambda_4 RATED_i + \epsilon_i\ , \quad (10)$$

Table 7 - Borrower controls

Variables	Coeff		t-value	Coeff		t-value
TYPES	-0.0767	***	(-7.4948)			
HHI				0.1636	***	(3.2608)
Borrower Controls	YES			YES		
R-Squared	0.0273			0.0234		

*** 1% significance level; ** 5% significance level; * 10% significance level

Similar to loan controls, the borrower controls explain more of the variation in the initial discount than the diversity measurements did by themselves, with R-squared between 2% and 3%. As before, the diversity proxies kept their expected signal, negative for $TYPES$ and positive for HHI, with a significance level of 1%.

These results suggest that the loan controls (table 6) contribute to explain a more significant part of the variance of the initial discount than the borrower controls (table 7).

4.4 Controlling for year fixed effects

To consider the effects of time in the discount, the fixed effects of the origination year of the loan were added to the model. The regressions and results are presented below:

$$DISCOUNT_i = \alpha + \beta \, TYPES_i \sum \gamma_j Year_{i,j} + \epsilon_i \,, \quad (11)$$

$$DISCOUNT_i = \alpha + \beta \, HHI_i + \sum \gamma_j Year_{i,j} + \epsilon_i \,, \quad (12)$$

Table 8 - Year Fixed Effects

Variables	Coeff		t-value	Coeff	t-value
TYPES	-0.0644	***	(-7.6052)		
HHI				0.0284	(0.6221)
Year Fixed Effects	YES			YES	
R-Squared	0.2107			0.2075	

*** 1% significance level; ** 5% significance level; * 10% significance level

From table 8, we conclude that the year fixed effects contribute more to increase the explanatory power of the model than the controls used before for loan and borrowers, with a R-squared close to 21%. The independent variable, $TYPES$, keep its negative relation with the $DISCOUNT$, with a significance level of 1%, as in the controls performed before. For some reason, in the regression with HHI, adding the year fixed effects makes the diversity measurement no longer significant. However, when all controls are run together in the next section, the significance returns, making this result difficult to explain.

These results suggests that the year of origination of the loan explain a significant part of the variance of the initial discount.

4.5 Investor diversity impact on the discount

The table 9 reports the results of the regression measuring the effect that the investor diversity measurements, $TYPES$ and HHI, have on the initial discount and subsequently the initial returns for the loans traded in the first month after origination. These regressions are presented in the section 3.3, equations (3) and (4). Panel A only includes observations where the original issue discount (OID) is available in the primary dataset, while Panel B represents our final sample of data that contains an approximation for the unavailable OIDs, as explained in section 3.2. All the observations in Panel A are also included in Panel B.

Table 9 - OLS Regression

	Panel A – With OID				Panel B – Full Sample			
Variables	Coeff		Coeff		Coeff		Coeff	
TYPES	-0.0098	(1)			-0.0434	***		
HHI			0.0078				0.1572	***
Loan Controls								
LOG AMOUNT	0.0022		0.0000		0.0610	***	0.0555	***
MATURITY	0.0015	***	0.0014	***	0.0160	***	0.0160	***
RATE	0.0746	***	0.0746	***	0.0424	***	0.0437	***
SECURED	-0.0200		-0.0192		0.1162	***	0.1330	***
SENIORITY	0.0000		0.0000		-0.3027	***	-0.2852	***
COVENANTS	0.0031		0.0023		-0.1497	***	-0.1566	***
DEAL AMENDED	-0.0354	**	-0.0353	**	-0.2476	***	-0.2458	***
CALL PROTECTION	0.0137		0.0134		0.2298	***	0.2322	***
ARRANGER SHARE	-0.0009	***	-0.0008	***	-0.0003		-0.0002	
PRIMARY PURPOSE	YES		YES		YES		YES	
Borrower Controls	YES		YES		YES		YES	
Year Fixed Effects	YES		YES		YES		YES	
Constant	0.3899	***	0.3756	***	-0.7205	***	-0.9220	***
Observations	5,896		5,896		17,455		17,455	
R-Squared	0.2077		0.2073		0.3129		0.3123	

Table 9 - Panel A uses the data with OID from the primary dataset. Panel B contains an approximation for the empty OIDs, using the average of the information from panel A, as explained in section 3.2. The full results of these regressions are presented in the section 6, tables 14 and 15.

*** 1% significance level; ** 5% significance level; * 10% significance level

(1) P-value equals to 0.105

The results of the regressions above for Panel A and Panel B, reach similar conclusions in terms of the signal for both diversity proxies, $TYPES$ and HHI. In panel B, the increase of significance level of the variables being tested should be a result of the increase in the number of observations.

In the regression on the final sample of data, panel B, the diversity proxy, $TYPES$, has a significant relation with 1% significant level with the initial discount of the loan. The negative sign, show as suggested, that with the increase in the number of different types of investors the initial discount decrease. This confirms the results expected by the theory, information produced by different types of investors and the complementarities between them increase the price efficiency, reducing the discount. The magnitude of the coefficient suggests that an increase of 1 additional investor type have an impact in the discount of around 1/10 of its mean or 1/33 of its standard deviation.

The HHI measure the concentration of shares per type of lender and its increase suggest a more concentrated loan. As expected, the sign of the coefficient is positive suggesting a relation of a higher discount if the ownership of the loan is more concentrated, with less investor diversity. In panel B, this variable also shows a significance level of 1%. The impact of adding one standard deviation in HHI, around 0.241 according to table 4, has a positive impact of 0.0379 in the discount. The magnitude of this impact is close to the one observed when adding a new type of investor, but with contrary signs.

The $LOG\ AMOUNT$ and $MATURITY$ variables were found to have a statistically significant positive effect on the discount. This might be explained by the higher risk taken by the lender for loan with higher amounts and longer terms that could be rewarded with a higher initial discount. Following the same logic, a loan with a higher rate usually reflects a borrower with more risk. That could also explain the positive and significant relation with the variable $RATE$.

The $SENIORITY$ and $COVENANTS$ variables, which protect the lender by reducing the risk exposure to a distressed borrower, show a negative correlation with the initial discount. Here too, the discount seems to be negatively correlated with the risk associated with the loan.

Contrary to our intuition, a statistically significant positive relation was found between the discount and if the loan was secured, $SECURED$. Intuitively, a secured loan would represent a lower risk to the lender which should result in a lower initial discount. A possible explanation for this positive relation could be a result of lenders requiring higher risk borrowers to provide collateralization.

The call protection is a mechanism that prohibits the borrower of calling back the security earlier. This could be an advantage for the lenders since the duration and expected interest of the loan would be more predictable. As a protection from the borrower, this was expected to be negatively correlated with the discount, which also didn’t happen in the results of table 9.

An amended deal is usually already present in the secondary market. The amendment of any of the initial conditions of the loans is made with knowledge of the price the market is paying for that loan which would result in a lower discount. The negative results with a 1% significance level found in table 9, with the variable $DEAL\ AMENDED$ confirms these expectations.

$ARRANGER\ SHARE$ is not significant in the Panel B regressions and there is no evidence to conclude that the correlation with the initial discount is different than zero. The results in Panel A are statically significant but its very low magnitude suggests the impact on the discount would be really small, especially since $ARRANGER\ SHARE$ only takes values between 0 and 1.

In panel A, the results before the assumptions for the empty OIDs are reported, concluding the same relation between the initial discount and the diversity proxies. The negative correlation between $TYPES$ and $DISCOUNT$ exists but with a lower significance level of 10.5%. The coefficient for the relation between HHI and $DISCOUNT$ is positive but it's not significant using this data set.

The R-squared for our final sample, tested in Panel B, was close to 31% in both regressions, improving from 21% in Panel A regressions. The difference between these Panels is the OIDs used and the size of the sample. The increase in the explanatory power of the models is assumed to be a result of these differences.

4.6 Robustness tests

In the previous sections we used the OLS model to measure the relation between the dependent and independent variables. Tests were performed for the OLS assumptions to identify any potential issues with our data.

The tests for Heteroscedasticity and Autocorrelation were the Breusch-Pagan-Godfrey and Breusch-Godfrey tests, respectively. The null hypothesis was rejected for both tests, rejecting homoscedasticity and no autocorrelation. To address these issues, the OLS was fitted using Heteroscedasticity and Autocorrelation Consistent (HAC) estimators.

The test for multicollinearity, was performed with the Variance Inflation Factor (VIF) and was less than 10 to all the variables. According to the rule of thumb the data doesn't seem to have multicollinearity issues. When creating the dummy variables, one of the categories was always excluded to avoid the dummy variable trap, a source of perfect multicollinearity (Brooks, 2008).

Normality was rejected with the Jarque-Bera test. On the other hand, the sample is large enough to use the Central Limit Theorem (CLT) and assume that the sample mean of the residuals would be approximately normally distributed (Ghasemi and Zahediasl, 2012).

Ramsey RESET test was used to test for linearity. The null hypothesis of a linear model was rejected suggesting some non-linear dependencies might exist between the dependent and independents variables that could result in biased estimators. Different transformations on the independent variables were tried, none of the transformations were able to pass the Ramsey RESET test. Non-linearity could affect the exact values of the estimates but maybe not their direction.

4.6.1 Controlling for Industry year fixed effects

To test the robustness of the results previously presented, some fixed effects were added. First, a new dummy variable was created for all the possible combinations between the industry of the borrower and the year when the loan was originated. The combination with highest number of observations was excluded and is considered the reference for the other dummies. The regressions and results are presented below:

$$DISCOUNT_i = \alpha + \beta\ TYPES_{i,j} + \sum \delta_k Loan_{i,k} + \sum \lambda_{l1} REGION_{i,l1} + \sum \lambda_{l2} RATING_{i,l2} + \lambda_{l3} RATED_{i,l3} + \sum \eta_m YEAR\ X\ INDUSTRY_{i,m} + \epsilon_i\ , \quad (13)$$

$$DISCOUNT_i = \alpha + \beta\ HHI_{i,j} + \sum \delta_k Loan_{i,k} + \sum \lambda_{l1} REGION_{i,l1} + \sum \lambda_{l2} RATING_{i,l2} + \lambda_{l3} RATED_{i,l3} + \sum \eta_m YEAR\ X\ INDUSTRY_{i,m} + \epsilon_i\ , \quad (14)$$

Table 10 - Robustness tests: Fixed Effects Industry Year

Variables	Coeff		t-value	Coeff		t-value
TYPES	-0.0354	***	(-4.1561)			
HHI				0.1391	***	(3.2545)
Loan Controls	YES			YES		
Borrower Controls *(Region, Rating and Rated)*	YES			YES		
Industry Year Fixed Eff.	YES			YES		
R-Squared	0.3658			0.3655		

*** 1% significance level; ** 5% significance level; * 10% significance level

The results presented in table 10, confirm the results obtained in previous sections. The correlation between the $DISCOUNT$ and $TYPES$ is negative with a significance level of 1%. Also, the positive effect of HHI was confirmed with the same level of significance.

The explanatory power of the model, R-squared, increased in relation to the one obtained in the full regression in table 9, which is expected because of the increased granularity of the new variables, Industry Year Fixed Effects, compared to $YEAR$ and $INDUSTRY$ by themselves.

4.6.2 Controlling for borrower fixed effects

Another robustness test of the results used was the borrower fixed effects. A dummy variable was created for each borrower, the borrower with higher number of observations was excluded. The regressions and results are presented below:

$$DISCOUNT_i = \alpha + \beta\ TYPES_i \sum \gamma_j BORROWER_{i,j} + \epsilon_i\ , \quad (15)$$

$$DISCOUNT_i = \alpha + \beta\ HHI_i + \sum \gamma_j BORROWER_{i,j} + \epsilon_i\ , \quad (16)$$

Table 11 - Robustness tests: Borrower Fixed Effects

Variables	Coeff	t-value	Coeff	t-value
TYPES	-0.0239 *	(-1.6528)		
HHI			0.0083	(0.1235)
Borrower Fixed Effects	YES		YES	
R-Squared	0.4491		0.4489	

*** 1% significance level; ** 5% significance level; * 10% significance level

The final combined dataset had 4,892 different borrowers, where 1,766 only had one loan. This robustness test limits the explanations of the variance in the $DISCOUNT$ to the borrowers with more than one loan. Testing for the borrower fixed effects, the correlation of $TYPES$ remain negative but with a lower significance level of 10%. In this case, no significant relation between $DISCOUNT$ and HHI was found.

As expected, the explanatory power of the model increases to around 45%, but it might have a problem of overfitting because of the thousands of dummy variables created. The adjusted R-squared accounts for the addition of each one of the new variables. The addition of thousands of new dummy variables for each borrower resulted in a lower adjusted R-squared of around 0.23.

5. Conclusion

This paper explored the under-pricing phenomenon in the syndicated loan markets, specifically the impact that investor diversity has on the discount in pricing from the origination stage compared to the first days of trading in the open market. Investor diversity was motivated by theory to be negatively correlated with under-pricing mainly through the interaction of additional information on market efficiency. The results gathered from the linear regressions described in the paper show that investor diversity, measured both through the number of investor types and the ownership concentration, has a significant impact on the under-pricing.

The two diversity measurements are shown to affect the discount in the expected directions, higher amount of industry types in the loan origination stage is negatively correlated with the discount while the ownership concentration has the opposite effect. This effect is robust to loan and borrower controls and year fixed effects, both individually and all combined.

The robustness of this effect was further tested by adding the combination of borrower industry and year fixed effects as well as borrower fixed effects. The effect was robust to industry year fixed effects but when the borrower fixed effects were tested, the concentration relation was no longer observable at the 10% significance level and the significance of the number of industry types was reduced from 1% to 10%.

The results should be interpreted with some precaution due to the findings of the Ramsey RESET test which show that there might be some non-linear dependencies between the controls and the discount which might bias our results. This limitation is thought to affect the exact values of the estimates but not their direction, allowing us to reach this conclusion.

The effect investor diversity has on the under-pricing of syndicated loans is relevant to borrowers and regulators, who both should be interested in a more efficient price discovery in the primary market. The paper also raises some questions to the relatively underdeveloped area of academic research on the secondary syndicated loan market, which is increasingly more important to understand due to its massive growth in the past few decades.

This paper was delimited to focus on the effect origination characteristics had on the initial returns but future research could study the pricing movements in the secondary loan market for a longer period of time. Also, the effect of both macroeconomic events like financial crisis, pandemics, wars and microeconomic events like credit rating changes or release of financial reports, on the secondary market prices could also be an interesting topic to study. Already, evident in Section 6, table 14 and 15, there seems to be an impact in the year fixed effects in the years following the financial crisis of 2008.

6. Appendix

Table 12 – Description of Variables

Variable Name	Description
Diversity proxies	
TYPES	Number of different types of investors per syndicate loan.
HHI	Herfindahl-Hirschman Index, measure of the concentration of the different lender types
Loan Controls	
LOG AMOUNT	Log of the total loan amount in millions of USD.
MATURITY	Original maturity of the loan in months.
RATE	Original reference rate + margin of the loan.
PRIMARY PURPOSE	Dummy variable equal to one if the primary purpose of the loan is Acquisition, General Purpose/Refinance, Leveraged Buyout, Sponsored Buyout, Takeover or Other.
SECURED	Dummy variable equal to one if loan is secured.
SENIORITY	Dummy variable equal to one if loan is senior.
COVENANTS	Dummy variable equal to one if loan has covenants.
AMENDED	Dummy variable equal to one if loan is amended.
CALL PROTECTION	Dummy variable equal to one if loan has a call protection.
ARRANGER SHARE	Share of loan retained by the arrangers.
Borrower Controls	
REGION	Dummy variable equal to one if the region of the borrower is Asia Pacific, Western Europe or other region.
RATED	Dummy variable equal to one if the company is rated.
RATING	Dummy variable equal to one if the company is rated AAA-A, BBB, BB+, BB, BB-, B+, B, B- or CCC-D.
INDUSTRY	Dummy variable equal to one if main industry of the borrower is Aerospace and defence, Automotive, Beverage, Food and Tobacco Processing, Business Services, Chemicals, Plastics and Rubber, Financial Services, General Manufacturing, Healthcare, Oil and Gas, Retail and Supermarkets, Services, Technology, Telecommunications, Utilities and Wholesale.
Year Fixed Effects	
YEAR	Dummy variable for each year between 2002 and 2020, except 2017, equal to one if the tranche was activated in that year.
Borrower Fixed Effects	
BORROWER	Dummy variable for each one of the borrowers.
Industry Year Fixed Effects	
YEAR X INDUSTRY	Dummy variable for each one of the combinations between years and industries of the borrower.

Table 13 - Full Descriptive Statistics

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
DEPENDENT VARIABLE					
ORIGIAL ISSUE DISCOUNT (OID)	99,021	0,832	99,026	99,026	99,026
MEAN QUOTE	98,469	6,423	99,000	100,000	100,500
DISCOUNT	-0,552	6,389	0,099	0,750	1,375
WINSORIZED DISCOUNT	0,403	1,462	0,099	0,750	1,375
DIVERSITY					
TYPES	2,738	1,329	2,000	3,000	3,000
HHI	0,548	0,241	0,372	0,500	0,625
LOAN					
LOG AMOUNT	5,705	1,128	5,011	5,704	6,429
MATURITY	66,173	21,853	54,000	70,000	84,000
RATE	5,505	2,607	3,799	5,250	7,186
Primary Purpose					
ACQUISITION	0,047	0,211	0,000	0,000	0,000
GENERAL PURPOSE/REFINANCE	0,047	0,212	0,000	0,000	0,000
LEVERAGED BUYOUT	0,146	0,353	0,000	0,000	0,000
OTHER PURPOSES	0,158	0,365	0,000	0,000	0,000
SPONSORED BUYOUT	0,066	0,248	0,000	0,000	0,000
TAKEOVER	0,076	0,265	0,000	0,000	0,000
SECURED	0,904	0,295	1,000	1,000	1,000
SENIORITY	0,016	0,125	0,000	0,000	0,000
COVENANTS	0,235	0,424	0,000	0,000	0,000
DEAL AMENDED	0,656	0,475	0,000	1,000	1,000
CALL PROTECTION	0,304	0,460	0,000	0,000	1,000
ARRANGER SHARE	64,523	36,127	33,333	66,667	100,000
BORROWER					
RATED	0,456	0,498	0,000	0,000	1,000
Rating					
AAA-A	0,005	0,069	0,000	0,000	0,000
B	0,107	0,309	0,000	0,000	0,000
B+	0,080	0,272	0,000	0,000	0,000
B-	0,035	0,183	0,000	0,000	0,000
BB	0,041	0,197	0,000	0,000	0,000
BB+	0,031	0,175	0,000	0,000	0,000
BB-	0,058	0,233	0,000	0,000	0,000
BBB	0,032	0,177	0,000	0,000	0,000
CCC-D	0,023	0,149	0,000	0,000	0,000
Region					
ASIA PACIFIC	0,010	0,101	0,000	0,000	0,000
EASTERN EUROPE/RUSSIA	0,016	0,125	0,000	0,000	0,000
OTHER REGIONS	0,010	0,100	0,000	0,000	0,000
WESTERN EUROPE	0,234	0,423	0,000	0,000	0,000
Major Industry					
AUTOMOTIVE	0,032	0,177	0,000	0,000	0,000

BEVERAGE, FOOD, AND TOBACCO	0,028	0,166	0,000	0,000	0,000
BUSINESS SERVICES	0,057	0,232	0,000	0,000	0,000
CHEMICALS, PLASTICS & RUBBER	0,055	0,227	0,000	0,000	0,000
FINANCIAL SERVICES	0,071	0,257	0,000	0,000	0,000
GENERAL MANUFACTURING	0,085	0,278	0,000	0,000	0,000
HEALTHCARE	0,093	0,291	0,000	0,000	0,000
OIL AND GAS	0,029	0,167	0,000	0,000	0,000
RETAIL & SUPERMARKETS	0,044	0,205	0,000	0,000	0,000
SERVICES	0,045	0,207	0,000	0,000	0,000
TECHNOLOGY	0,086	0,280	0,000	0,000	0,000
TELECOMMUNICATIONS	0,041	0,199	0,000	0,000	0,000
UTILITIES	0,027	0,162	0,000	0,000	0,000
WHOLESALE	0,038	0,191	0,000	0,000	0,000
YEAR FIXED EFFECTS					
2001	0,001	0,036	0,000	0,000	0,000
2002	0,008	0,090	0,000	0,000	0,000
2003	0,008	0,091	0,000	0,000	0,000
2004	0,023	0,149	0,000	0,000	0,000
2005	0,042	0,200	0,000	0,000	0,000
2006	0,061	0,239	0,000	0,000	0,000
2007	0,077	0,267	0,000	0,000	0,000
2008	0,019	0,137	0,000	0,000	0,000
2009	0,021	0,145	0,000	0,000	0,000
2010	0,034	0,182	0,000	0,000	0,000
2011	0,047	0,212	0,000	0,000	0,000
2012	0,066	0,248	0,000	0,000	0,000
2013	0,087	0,282	0,000	0,000	0,000
2014	0,075	0,263	0,000	0,000	0,000
2015	0,053	0,223	0,000	0,000	0,000
2016	0,049	0,215	0,000	0,000	0,000
2018	0,105	0,307	0,000	0,000	0,000
2019	0,076	0,266	0,000	0,000	0,000
2020	0,054	0,226	0,000	0,000	0,000

Table 14 - Full Results OLS Regression Panel A

	Panel A					
Variables	Coeff		t-value	Coeff		t-value
TYPES	-0.0098		(-1.6231)			
HHI				0.0078		(0.3014)
Loan Controls						
LOG AMOUNT	0.0022		(0.2734)	0.0000		(-0.0013)
MATURITY	0.0015	***	(2.9268)	0.0014	***	(2.7723)
RATE	0.0746	***	(17.0885)	0.0746	***	(17.0641)
SECURED	-0.0200		(-0.4451)	-0.0192		(-0.429)
SENIORITY	0.0000		(0.7155)	0.0000		(-0.6338)
COVENANTS	0.0031		(0.1883)	0.0023		(0.1394)
DEAL AMENDED	-0.0354	**	(-2.5553)	-0.0353	**	(-2.5472)
CALL PROTECTION	0.0137		(0.7728)	0.0134		(0.7566)
ARRANGER SHARE	-0.0009	***	(-4.1503)	-0.0008	***	(-3.8442)
PRIMARY PURPOSE						
ACQUISITION	0.0465	*	(1.6613)	0.0451		(1.614)
GEN. PURP./REFINANCE	0.0209		(0.6599)	0.0206		(0.6503)
LEVERAGED BUYOUT	0.1100	***	(4.6037)	0.1082	***	(4.5227)
OTHER PURPOSES	0.0951	***	(4.6281)	0.0939	***	(4.5674)
SPONSORED BUYOUT	0.0622	***	(2.5909)	0.0607	**	(2.5262)
TAKEOVER	0.0312		(1.333)	0.0297		(1.2703)
Borrower Controls						
REGION						
ASIA PACIFIC	-0.0039		(-0.0557)	-0.0031		(-0.0456)
EAST. EUROPE/RUSSIA	-0.1297		(-1.0722)	-0.1273		(-1.0404)
OTHER REGIONS	0.0630		(0.871)	0.0662		(0.917)
WESTERN EUROPE	-0.0211		(-1.0445)	-0.0181		(-0.8982)
INDUSTRY						
AUTOMOTIVE	0.0359		(0.926)	0.0347		(0.8944)
BEVER., FOOD, TOBACCO	-0.0124		(-0.3138)	-0.0132		(-0.3321)
BUSINESS SERVICES	-0.0551	**	(-1.9666)	-0.0559	**	(-1.993)
CHEMIC, PLASTIC	0.0285		(0.9783)	0.0281		(0.9659)
FINANCIAL SERVICES	-0.0001		(-0.0024)	0.0009		(0.0344)
GENERAL MANUFACTUR.	0.0192		(0.7594)	0.0201		(0.796)
HEALTHCARE	-0.0131		(-0.5722)	-0.0138		(-0.602)
OIL AND GAS	0.1596	***	(3.6489)	0.1610	***	(3.678)
RETAIL & SUPERMARK.	-0.0385		(-1.1389)	-0.0396		(-1.1704)
SERVICES	0.0056		(0.1878)	0.0058		(0.1943)
TECHNOLOGY	-0.0213		(-0.945)	-0.0199		(-0.8832)
TELECOMMUNICATIONS	-0.0539		(-1.5708)	-0.0531		(-1.5486)
UTILITIES	0.0415		(1.0402)	0.0424		(1.0643)
WHOLESALE	0.0295		(0.8092)	0.0294		(0.8064)
RATING						
AAA-A	0.0000		(0.8665)	0.0000		(-0.2542)
B	0.0139		(0.412)	0.0135		(0.3991)

B+	0.0211		(0.5798)	0.0212		(0.5831)
B-	0.0918	**	(2.1011)	0.0911	**	(2.084)
BB	0.0205		(0.504)	0.0188		(0.4625)
BB+	-0.0236		(-0.5527)	-0.0240		(-0.5612)
BB-	0.0602		(1.6081)	0.0591		(1.5772)
BBB	-0.1269	***	(-2.7739)	-0.1288	***	(-2.8135)
CCC-D	-0.0187		(-0.2762)	-0.0192		(-0.284)
Year Fixed Effects						
2001	0.0000	***	(-8.8815)	0.0000		(-1.5167)
2002	0.0000	***	(-4.0856)	0.0000	**	(2.4253)
2003	0.0000	***	(-4.8011)	0.0000	***	(4.9534)
2004	0.0000	***	(-7.5263)	0.0000	***	(-4.6727)
2005	0.0000	***	(3.8911)	0.0000	*	(-1.9034)
2006	0.0000	***	(-5.0842)	0.0000		(-0.8639)
2007	-0.4765	***	(-6.0163)	-0.4758	***	(-5.9636)
2008	-0.1059		(-0.8716)	-0.1038		(-0.8546)
2009	0.4801	***	(6.0207)	0.4759	***	(5.9738)
2010	0.3168	***	(6.9843)	0.3146	***	(6.9494)
2011	0.0501		(1.254)	0.0488		(1.219)
2012	0.1497	***	(4.6461)	0.1487	***	(4.6103)
2013	0.2240	***	(9.15)	0.2233	***	(9.1184)
2014	0.0145		(0.5631)	0.0137		(0.5341)
2015	-0.0384		(-1.2331)	-0.0383		(-1.2326)
2016	0.0249		(0.7272)	0.0240		(0.7006)
2018	-0.1607	***	(-7.7379)	-0.1617	***	(-7.7848)
2019	-0.1850	***	(-7.8883)	-0.1867	***	(-7.9655)
2020	-0.0650	**	(-2.073)	-0.0676	**	(-2.1576)
Constant	0.3899	***	(4.7206)	0.3756	***	(4.3769)
Observations	5896			5896		
R-Squared	0.2077			0.2073		

*** 1% significance level; ** 5% significance level; * 10% significance level

Table 15 - Full Results OLS Regression Panel B

	Panel B					
Variables	Coeff		t-value	Coeff		t-value
TYPES	-0.0434	***	(-4.9918)			
HHI				0.1572	***	(3.607)
Loan Controls						
LOG AMOUNT	0.0610	***	(5.4045)	0.0555	***	(5.4045)
MATURITY	0.0160	***	(22.3924)	0.0160	***	(22.3924)
RATE	0.0424	***	(7.5119)	0.0437	***	(7.5119)
SECURED	0.1162	***	(2.7123)	0.1330	***	(2.7123)
SENIORITY	-0.3027	***	(-3.4262)	-0.2852	***	(-3.4262)
COVENANTS	-0.1497	***	(-5.1814)	-0.1566	***	(-5.1814)
DEAL AMENDED	-0.2476	***	(-10.5652)	-0.2458	***	(-10.5652)
CALL PROTECTION	0.2298	***	(9.664)	0.2322	***	(9.664)
ARRANGER SHARE	-0.0003		(-0.8892)	-0.0002		(-0.5414)
PRIMARY PURPOSE						
ACQUISITION	0.0364		(0.8037)	0.0353		(0.8037)
GEN. PURP./REFINANCE	0.0146		(0.301)	0.0089		(0.301)
LEVERAGED BUYOUT	-0.1994	***	(-5.7608)	-0.2043	***	(-5.7608)
OTHER PURPOSES	-0.0126		(-0.385)	-0.0170		(-0.385)
SPONSORED BUYOUT	-0.1758	***	(-4.2833)	-0.1790	***	(-4.2833)
TAKEOVER	-0.1352	***	(-3.4158)	-0.1397	***	(-3.4158)
Borrower Controls						
REGION						
ASIA PACIFIC	-0.2850	**	(-2.4174)	-0.2853	**	(-2.4174)
EAST. EUROPE/RUSSIA	-0.0648		(-0.7731)	-0.1242		(-0.7731)
OTHER REGIONS	-0.0010		(-0.0109)	-0.0128		(-0.0109)
WESTERN EUROPE	-0.2137	***	(-6.6595)	-0.2162	***	(-6.6595)
INDUSTRY						
AUTOMOTIVE	0.0505		(0.7695)	0.0494		(0.7695)
BEVER., FOOD, TOBACCO	0.2258	***	(3.5688)	0.2191	***	(3.5688)
BUSINESS SERVICES	0.0260		(0.5584)	0.0267		(0.5584)
CHEMIC, PLASTIC	0.0599		(1.26)	0.0610		(1.26)
FINANCIAL SERVICES	0.2070	***	(4.9291)	0.2068	***	(4.9291)
GENERAL MANUFACTUR.	0.0718	*	(1.7918)	0.0752	*	(1.7918)
HEALTHCARE	0.1768	***	(4.6615)	0.1787	***	(4.6615)
OIL AND GAS	0.0417		(0.5723)	0.0413		(0.5723)
RETAIL & SUPERMARK.	-0.0269		(-0.4664)	-0.0319		(-0.4664)
SERVICES	0.0041		(0.0802)	0.0090		(0.0802)
TECHNOLOGY	0.0890	**	(2.1887)	0.0937	**	(2.1887)
TELECOMMUNICATIONS	0.0078		(0.1388)	0.0099		(0.1388)
UTILITIES	-0.1092		(-1.6255)	-0.1055		(-1.6255)
WHOLESALE	-0.1085	*	(-1.7324)	-0.1083	*	(-1.7324)
RATING						
AAA-A	0.2832	**	(2.4249)	0.2661	**	(2.4249)
B	0.2058	***	(3.291)	0.2040	***	(3.291)

B+	0.2708	***	(4.1018)	0.2712	***	(4.1018)
B-	0.0346		(0.4191)	0.0303		(0.4191)
BB	0.3093	***	(4.2918)	0.3032	***	(4.2918)
BB+	0.3287	***	(4.0865)	0.3208	***	(4.0865)
BB-	0.2485	***	(3.478)	0.2451	***	(3.478)
BBB	0.4206	***	(5.4391)	0.4045	***	(5.4391)
CCC-D	-0.2728	**	(-2.5453)	-0.2707	**	(-2.5453)
Year Fixed Effects						
2001	-0.6932	*	(-1.9467)	-0.7298	*	(-1.9467)
2002	-1.1079	***	(-6.3617)	-1.1400	***	(-6.3617)
2003	-0.7510	***	(-4.4846)	-0.7859	***	(-4.4846)
2004	0.3595	***	(4.9777)	0.3279	***	(4.9777)
2005	0.4055	***	(6.9551)	0.3834	***	(6.9551)
2006	0.3747	***	(7.6881)	0.3593	***	(7.6881)
2007	0.0108		(0.2098)	0.0044		(0.2098)
2008	-2.1586	***	(-22.9171)	-2.1637	***	(-22.9171)
2009	-2.2697	***	(-23.7026)	-2.2764	***	(-23.7026)
2010	-0.7718	***	(-9.798)	-0.7848	***	(-9.798)
2011	-0.5762	***	(-9.1086)	-0.5727	***	(-9.1086)
2012	-0.4289	***	(-7.3685)	-0.4225	***	(-7.3685)
2013	0.1276	***	(2.9609)	0.1336	***	(2.9609)
2014	-0.0186		(-0.4452)	-0.0130		(-0.4452)
2015	-0.1822	***	(-3.7697)	-0.1789	***	(-3.7697)
2016	-0.2867	***	(-5.3227)	-0.2880	***	(-5.3227)
2018	-0.2069	***	(-5.9127)	-0.2089	***	(-5.9127)
2019	-0.4856	***	(-11.4708)	-0.4859	***	(-11.4708)
2020	-1.2366	***	(-19.7807)	-1.2386	***	(-19.7807)
Constant	-0.7205	***	(-6.9268)	-0.9220	***	(-6.9268)
Observations	17455			17455		
R-Squared	0.3129			0.3123		

*** 1% significance level; ** 5% significance level; * 10% significance level

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