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- The Evolution of the Global Corporate Loan Market: A Network Approach

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Abstract

We empirically explore the global corporate loan market. Collaboration among loan lead arrangers through syndicated loans has contributed to the development of a complex social network of banks, but how does this complexity affect syndicate structure, i.e. given the social network of banks, how does the loan syndicate look? We observe that complex loans to opaque borrowers are issued by syndicates with members in structurally important positions within the social network of lead arranging banks. Our innovation in this study is that we characterize banks according to their structural position in the social network formed by lead arrangers in the global corporate loan market.

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The global corporate loan market and syndicate formation: A network perspective

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Preliminary version, comments welcome

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Abstract

We empirically explore the global corporate loan market. Collaboration among loan lead arrangers through syndicated loans has contributed to the development of a complex social network of banks, but how does this complexity affect syndicate structure, i.e. given the social network of banks, how does the loan syndicate look? We observe that complex loans to opaque borrowers are issued by syndicates with members in structurally important positions within the social network of lead arranging banks. Our innovation in this study is that we characterize banks according to their structural position in the social network formed by lead arrangers in the global corporate loan market.

Keywords: Global corporate loans, syndicated lending, social networks.

1 Introduction

The corporate loan market has evolved over the past 20 years. We observe that not only the number and types of loans issued on a yearly basis has changed, but also the composition of the banks issuing them. Between 1990 and 2010, the ratio of loans arranged by multiple lead arrangers rose from just 13% to more than 80%. In the face of such an evolving corporate loan market in which banks are prone to syndicate to raise loans, we expect syndicate formation to be a relevan question. In this research, we are therefore interested in the following question: given the complexity of the global corporate loan market, how does the loan syndicate look? To answer this question, this study investigates the structure and evolution of the global corporate loan market, which includes syndicated loans.

Loan syndication is a process involving a group of banks, that jointly make a loan to a single borrower. Members of the syndicate fall into one of two groups, lead arrangers and participant lenders. Lead arrangers are active syndicate members that take responsibility to conduct due diligence on the borrower, negotiate loan details, arrange documentation and recruit the passive participant banks to fund the loan. During the life of the loan, lead arrangers monitor the borrower and share their findings with the participant lenders, hold collateral, administer the loan and handle disbursements and repayments. Due to their active role in raising loans, we focus our study on lead arrangers. The total number of lead arrangers is large and the increasing rates at which banks syndicate, render a complex network of banks consisting of lead arrangers that are linked to each other when they co-arrange a loan. According to the Loan Pricing Corporation Dealscan database, the share of loans that are arranged by multiple lead arrangers increased from 13% to 83% between 1990 and 2010, respectively. This evidence suggests that through time, more banks syndicate loans thus contributing to a larger, denser and more complex network of lead arrangers.

A natural question that should be addressed is why would multiple arrangers syndicate in the first place? In a syndicate, multiple arrangers combine their expertise (Das and Nanda, 1999; Sah and Stiglitz, 1986). At the same time, the various tasks can be allocated among the arrangers to avoid duplication of efforts, thus reducing each arranger's effort costs. Such knowledge and effort sharing is especially valuable when the loan is complex and monitoring needs are higher. For example, a line of credit to a borrower with whom the arranger has an established lending relationship is easy to set up and monitor. Thus, benefits of effort sharing from forming a syndincate are likely to be small. In contrast, a project finance loan consists of an extensive set of contracts including the credit agreement, security documents, equity contribution agreement, intercreditor agreement, hedging agreements, and project agreements (Gatti, 2012). The required expertise for project finance loans is both more specific and extensive. Thus, benefits of knowledge sharing are large and banks should have a strong incentive to jointly arrange such a loan. Hence, we expect loan syndication to be beneficial under two circumstances, when there is a higher need to mitigate informational asymmetry, e.g. higher monitoring needs, and when different competitive and complementary advantages are beneficial to carry out the loan.

2 Literary Review

Syndicate formation has been analyzed from the perspectives of capital and liquidity management, lending specialization, information asymmetry, as well as relationships and reputation. Syndicated lending is an effective tool for banks to diversify their loan portfolios and manage their risk. Additionally, the flexibility in determining the size of the lending share allows capital -or liquidity-constrained banks to participate. Participant banks may also be motivated to join a syndicate as a result of their lack of experience in specific loan types or markets (Dennis and Mullineaux, 2000; Pennachi, 1988; Schure et al., 2005; Simons, 1993; Wilson, 1968).

Another stream of literature highlights the importance of information asymmetries between the borrower and the syndicate (Bosch and Steffen, 2011; Dennis and Mullineaux, 2000; Esty and Megginson, 2003; Francois and Missonier-Piera, 2007; Ivashina, 2009; Jones et al., 2005; Lee and Mullineaux, 2004; Simons, 1993; Das and Nanda, 1999; Sufi, 2007). Empirical evidence indicates that joint arrangement of loans reduces information asymmetries over the borrowing firm and the service being offered, e.g. type of loan (Das and Nanda, 1999). In other words, syndicates are formed to bring together the complementary skills of arrangers in various duties of the loan syndication process, and to reduce information asymmetries about the quality of the borrowing firm (Sufi, 2007).

We recognize the importance of information asymmetry problems in shaping the structure of the syndicate and contrast them with the benefits of syndication, which include knowledge and monitoring capital needs. For example, banks may syndicate with the purpose of reducing information asymmetries about the borrower. Lead arrangers are the only syndicate members that interact with the borrower and thus need to be best informed about who the borrower is and the risks associated with lending to her.

The work presented here extends the existing research on syndicated loans in several new directions. First, we study the evolution of the global corporate loan market in terms of network complexity, with an emphasis on lead arrangers. The lead arranger choice analysis conducted in this paper helps enrich the understanding of how the market has evolved in terms of skills and reputation development of the lead arrangers. Second, this paper explores syndicate structure in terms of the network characteristics of lead arrangers. By following this approach, we extend the literature of syndicate structure, which typically focuses on syndicate size and lead arranger loan shares, through the use of network measures. Finally our study adds to the emerging literature that applies social network analysis to the study of financial markets.[1]

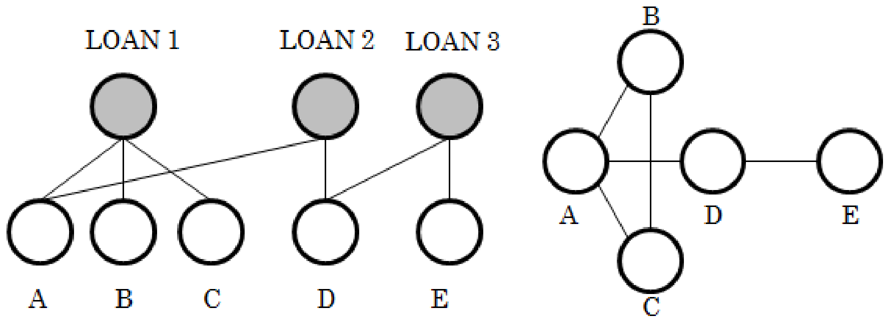
The primary focus of this paper is to study how information asymmetry affects syndicate structure, and how such syndicate structure has changed over time in lieu of a more complex network of lead arrangers. The current literature in syndicate structure offers diverging conclusions when addressing mitigation of information asymmetry through syndication. Lee and Mullineaux (2004) and Sufi (2007) find that when the borrowing firm requires more thorough due diligence and monitoring, the resulting syndicate is larger. Larger syndicates arise because the opaqueness associated with the loan being arranged implies larger monitoring efforts that can only be alleviated by having multiple lead arrangers sharing in the costs of of information collection, processing and loan monitoring. On the other hand, Esty and Megginson (2003) and Nini (2004) find that loans to borrowers from opaque markets are arranged by smaller syndicates. Smaller syndicates facilitate changing loan terms in case strategic default is suspected. What these studies lack is taking into account the extent to which banks work together and share information, i.e. their network centrality. For example, banks that are more central in a network tend to be more active in loan syndication and hence better candidates for arranging loans in the presence of information asymmetry.

3 The Lead Arranger Network

The lead arranger network is an example of an affiliation network with binary relationships between members of two sets of items. Our two sets are lead arrangers and global corporate loans. The binary relation that connects them is the "arranged" relation, see Figure 1a. Since we are interested in the loan co-arrangement process, or in other words the patterns of ties within the arrangers set, we define loan co-arrangement to represent the global corporate loan market network. Loan co-arrangement implies arrangement of the same loan, see Figure 1b. In our network, the nodes represent lead arrangers and the links represent co-arrangement. This means, that two nodes in the network are linked if they have co-arranged a loan, i.e. they are in the same syndicate.

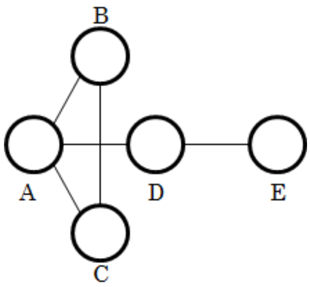
Social networks are characterized by a set of measures that explain their size and complexity. Size is measured by the number of nodes in the network, i.e. the number of distinct lead arrangers that belong to the corporate loan network (Hanneman and Riddle, 2005). We particularly focus on

[1]See Allen and Babus (2008) for a survey of this literature. Later studies include Hale (2011) and Minoiu and Reyes (2011).



(a) Affiliation Network (b) Co-arrangement Network

Figure 1: **Network creation**. The left figure is an exemplification of an affiliation network of loan syndication. It depicts three loans arranged by 3, 2 and 2 arrangers, respectively. The grey node represents loan affiliation and the nodes in white represent the members. The figure on the right depicts the transformation of the affiliation network on the right to a co-arrangement network in which arrangers that have co-arranged loans are linked to each other.



Network Metrics		
Node	Degree	Closeness
A	3	1.25
B	2	1.75
C	2	1.75
D	2	1.5
E	1	2.25

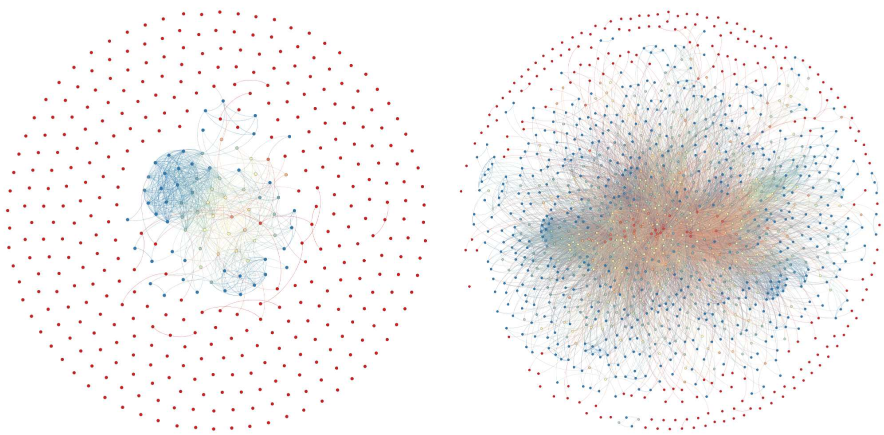
Figure 2: **Network representation and network metrics**
Representation of a simple connected network with 5 nodes. Its corresponding network metrics, such as degree and closeness centrality are presented on the table on the right. Node A has the highest degree measure since it is the one with the largest number of links. Node E has the largest closeness centrality because its shortest path to reach everybody else in the network is the smallest, whereas A has the smallest closeness centrality since the path to reach all other nodes in the network is the longest, i.e. A is the farthest node in the network.

two complexity measures, *degree* and *closeness centrality*. Figure 2 represents a simple network with 5 nodes, and the table on the right shows the degree and closeness centrality measures for each node in the simple network. Degree indicates the number of direct links a node has. It is a measure that quantifies the connectedness of the network, and thus reflects the level of syndication among lead arrangers. Nodes with the largest degree measures are the most active lead arrangers in the network. These are the lead arrangers that tend to co-arrange loans more often and hence are more experienced in the co-arrangement process.

The *closeness centrality* of a node in a network is a measure of its structural importance and quantifies the prominence of an individual node embedded in a network. *Closeness centrality* assumes that nodes that are able to reach other nodes at short-path lengths are in favored positions. This is an indicator of a node's position with respect to the other nodes in the network. In the social networks literature, closeness centrality is typically used as a proxy for reputation. Nodes with a larger closeness centrality have the advantage of being central, but they also have the disadvantage that any news about them is quickly spread throughout the network. So, nodes with a large closeness centrality have the incentive to not behave in an opportunistic manner such that negative news do not spread and they can preserve their reputation levels. This means for nodes with a large closeness centrality, it is in the best of their interest to do their best in the loan arrangement process, especially in an environment where repeated interactions often occur, such as in the corporate loan market. Hence, we expect that when there is a large information asymmetry, then banks with a high closeness centrality would be beneficial to have as lead arrangers in the syndicate. In figure 2, node E has the largest closeness centrality and node A has the smallest closeness centrality. This means that it is in the best of node E's interest to perform as a lead arranger.

4 Network evolution

In order to obtain complete information on the topology of the network, we use all global corporate loans that have been raised between 1990 and 2010 as reported in the Loan Pricing Corporation's Dealscan database. In this section, we investigate the topology and evolution of the social network formed by arrangers of global corporate loans. Figure 3a and 3b illustrate the corporate loan market as a network representation in two time periods, 1990 and 2010. One can observe that in 20 years, the corporate loan market has grown in terms of size and activity levels. Between these two years, the number of nodes in the network increased by a factor of 3, from 440 in 1990 to 1,322 in 2010.[2] The number of links between the nodes increased by a factor of 22 from 1,394 in 1990 to 31,548 in 2010.



(a) 1990

(b) 2010

Figure 3: **Network representation of the global corporate loan market.**
The left figure is from 1990, and the figure on the right is from 2010. Each node represents a lead arranger. Each link represents joint loan arrangement.

[2]The increase in the number of nodes for the first 7 years can be due to improvements in the database coverage, especially between 1990 and 1993.

Figure 4: **Evolution of centrality measures**
This figure depicts the evolution of the corporate loan market between 1990 and 2010. The metrics herein displayed are closeness and degree.

The syndicated lending network clearly shows that both the average degree and closeness centrality of lead arrangers have increased with time, as can be seen in figure 4. This tells us two things. First, the network has become more connected, not only in terms of direct co-arranging, but also in terms of indirect linkages with the network being better interconnected overall. On the average, the number of links per node increased from 3.17 to 23.86 links. In addition, we observe that the average bank arranges 1.30 loans per year. This simply indicates that lead arrangers have become more active in the loan syndication market and hence the increasing density of links in the network. The average degree of lead arrangers increased form 9 in 1990 to 19 in 2010. The top 5 banks with the largest degree measures in 2010 include Royal Bank of Scotland, HSBC, Bank of Tokyo-Mitsubishi, Credit Agricole Corporate & Investment Bank, and BNP Paribas. These are the most active lead arrangers and they are also among the largest banks in the market. These are banks that can leverage economies of scale to actively syndicate multiple loans with other banks. Lead arrangers that syndicate more often gain skills in the loan syndication process that are beneficial in future loan arrangements.

5 Hypotheses

Our main premise is that more experienced and reputable syndicates are formed when the loan requires larger arranging efforts, such as higher due diligence and monitoring. We identify two high levels at which the loan requires larger arranging efforts, that is when the loan is complex and when the borrower is opaque. To be more precise, we characterize the complexity of a loan through the way in which it has been structured, and by its type and purpose. Some loan types and purposes pose higher risk than others, and thus, we deem them as complex. Likewise, we recognize that a borrower can be opaque in different dimensions, availability of public information and lead arranger to borrower experience, which is rather a source of private or internal information. Reputation and experience considerations regarding the lead arrangers in the syndicate are likely to play an important role because lead arrangers and participant lenders are repeat players with long organizational memories (Lee and Mullineaux, 2004; Champagne and Kryzanowski, 2007).

We employ the information on the past performance of lead arrangers from the social network formed through lead arranger syndication. According to Lee and Mullineaux (2004) syndicating banks use information about lead arrangers in forms of rankings which assist in making decisions about future syndicate collaboration. Below, we elaborate on the implications of each loan complexity and borrower opaqueness dimension and propose a set of hypotheses. We propose a different hypothesis for each compelxity and opaqueness dimensions.

5.1 Credit Risk

Credit risk or in other words, the possibility that the borrowing firm will default on the loan is expected to affect the structure of the syndicate of lead arrangers. We expect an increase in due diligence and monitoring needs, which translates into reputable and/or experienced lead arrangers syndicating the loan. Loan defaults imply that in the event of financial distress, the loan has to be re-structured and hence a more experienced lead arranger is more likely to be familiar with this process while at the same time, it is more convenient for her to transfer her monitoring skills onto another deal. On the other hand, when a loan is issued to high-risk borrower, then it is not in the best of her interests for the reputable lead arranger to be part of the syndicate since defaults damage the reputation status of lead arrangers. Hence, our hypotheses for credit risk are:

Hypothesis 1A (Reputation): *When the borrowing firm has an associated credit risk, then the needs for due diligence and monitoring efforts will take place in the forms of reputable lead arrangers in the syndicate.*

Hypothesis 1B (Experience): *When the borrowing firm has an associated credit risk, then the needs for due diligence and monitoring efforts will (will not) take place in the forms of experienced lead arrangers in the syndicate.*

Our first set of risk measures are MULTIPLE TRANCHE, a dummy variable that is equal to one when the loan has multiple tranches and zero otherwise; REVOLVING CREDIT, a dummy variable that is equal to one when the loan type is of revolving credit nature and zero otherwise; and, REFINANCE, another dummy variable that is equal to one when the loan is a refinance loan. The second set of risk measures include MATURITY and TERM. Maturity measures the life of the loan. Evidence on whether longer-maturity loans have less or more credit risk is mixed. Term is a dummy variable that is equal to one if it is a term loan. A term loan can be as short as one year and as long as 30 years. While these measures do not explain much about the defaulting nature of the borrower, they convey information about the risk associated with the loan being raised. For example, a multiple tranche loan is associated with deals of different risk levels. A positive coefficient in these dummy variables indicate that credit risk is alleviated via more experienced and/or reputable lead arrangers during the due diligence and monitoring processes to prevent default on the loan.

5.2 Information about the Borrower

Quantity and quality of information about the borrower affect syndicate structre (Dennis and Mullineaux, 2000; Lee and Mullineaux, 2004). According to Lee and Mullineaux (2004), finance theory predicts that borrowers requiring more due diligence and monitoring efforts result in syndicate members having the capability and capacity to focus on the monitoring tasks of the loan. In terms of syndicate size, this means that the syndicate is small with each lead arranger retaining a larger share of the loan. With respect to our experience and monitoring measures, we expect the following:

Hypothesis 2A (Reputation): *When quantity and quality of information about the borrowing firm is lacking, then the needs for due diligence and monitoring efforts will take place in the forms of reputable lead arrangers in the syndicate.*

Hypothesis 2B (Experience): *When quantity and quality of information about the borrowing firm is lacking, then the needs for due diligence and monitoring efforts will (will not) take place in the forms of experienced lead arrangers in the syndicate.*

More reputable lead arrangers are expected to exert the required efforts in arranging such loan in order to maintain their reputable position in the network of lead arrangers. On the other hand, experienced lead arrangers may be able to retrieve information about the borrower from a previous deal or simply they have the experience in working more in the presence of information asymmetries. However, these experienced lead arrangers that arrange multiple loans at the same time, may not have the scope or scale to invest in the required levels of due dilingence and monitoring due to its other loan commitments, so lead arrangers that are less experienced may be preferred to arrange a loan with low quantity and quality of information about the borrower.

The first proxies for information are RATING, a dummy variable equal to one if the borrower has a credit rating and zero otherwise, and PUBLIC, a dummy equal to one if the borrower has a ticker symbol and zero otherwise. The next set of proxies involve less public information, such as PREVIOUS BORROWER, a dummy variable equal to one if the borrower has had a previous loan with any of the current syndicate members and zero otherwise, and NUMBER OF LOANS WITH SAME LEAD ARRANGER, a count variable that indicates the maximum number of deals with any of the syndicate members currently arranging the loan. The underlying argument that higher-quality information is available about firms that have credit ratings (Lee and Mullineaux, 2004). Moreover, a borrowing history with lead arranger members in the syndicate offer complementary non-public information about the borrower and thus putting the syndicate in a better-informed position when arranging and monitoring the loan.[3] In particular because lead arrangers have direct lending relationships with borrowers. A positive coefficient on these dummies indicates syndicates with experienced and/or more reputable lead arrangers form when the borrower is a well-known firm. If the coefficient of the information dummies are negative in the "Experience" model, it simply suggests that having lead arrangers that are less active in the syndicate lending market serve as better monitors since they co-arranger fewer loans and thus have sufficient monitoring capital available to invest in the current loan.[4]

5.3 Project Risk

Among the different purposes for which a loan may be used, there are three categories that can be associated with specific projects and most of the time these projects pose high risks. These are REAL ESTATE, MERGERS AND ACQUISITIONS (M&A), and PROJECT FINANCE loans. These

[3]We also have information about the total number of loans issued to a specific borrower as an additional measure of information. However, this measure is not available to all lead arrangers unless one same lead arranger has issued all loans to the same borrower and is aware of this or all loans have been raised by all lead arranger members in the syndicate.

[4]There is a sub-sample of borrowers for which we have additional information about the borrower, such as sales. We use the log of borrower sales as an additional proxy for information availability

loans are typically larger and the returns of these investments are unknown and hence pose high risk. For example, real estate loans have been considered risky as early as 1993, much earlier than the 2007/2008 financial crisis which severely affected the real estate sector (Simons, 1993; Jones et al., 2005). M&A loans are used for risky projects since the expected returns of the acquisitions or mergers for which they are used are unknown and these loans are also typically large. In addition, they usually have to be arranged whithin a reasonable period of time due to the sensitivity associated with this type of projects. In addition, who arranges this type of loans is very important because in many occasions, M&As may have not been publicly announced and discretion is necessary. Last, project finance loans have been target of much research, such as (Esty and Megginson, 2003; Nini, 2004) and their risk levels depend on whether or not the country in which the project is being developed has a sufficient legal enforcement system (Esty and Megginson, 2003). We therefore expect:

Hypothesis 3A (Reputation): *When the loan being syndicated has project risk, then the needs for due diligence and monitoring efforts will take place in the forms of reputable lead arrangers in the syndicate.*

Hypothesis 3B (Experience): *When the loan being syndicated has project risk, then the needs for due diligence and monitoring efforts will take place in the forms of experienced lead arrangers in the syndicate.*

The three different variables measuring project risk are dummy variables that are equal to one when the loan purpose is equal to any of the three categories and zero otherwise. A positive coefficient on any of these dummies suggests that in the presence of high project risk, reputable and experienced lead arrangers are leveraged to conduct due diligence and monitoring needs on the loan. For example, project finance loans require extensive administrative work, and an experienced lead arranger will certainly facilitate this process. Likewise, if the loan is used to finance an M&A, a reputable lead arranger will be able to conduct its tasks in a satisfactory manner and is expected to handle all sensitive information accordingly. Alternatively, a negative coefficient indicates that in lieu of high project risk a reputable lead arranger prefers to not jeopardize its position and not participate in such project. On the other hand, an experienced and active lead arranger is not able to offer the required effort that such risky loan calls for.

5.4 Loan Structure

Loans can be structured in such a way that risk or probability of default is minimized, for example via guarantees, and/or financial covenants[5]. During the life of the loan, the lead arranger has to enforce the financial covenants of the loan (Sufi, 2007). Guarantees, collateral and loan covenants offer the possibility of explicitly linking pricing to corporate events (rating changes, debt servicing). Collateralization and guarantees are more often used for emerging market borrowers, while covenants are much more widely used for borrowers in industrialized countries. In general, lead arrangers must have the proper incentives to engage in diligent monitoring of the collateral, and thus agency problems might therefore be more severe on secured loans. Hence, we should expect the following:

Hypothesis 4A (Reputation): *If the loan structure is such that it minimizes probability of default, then the needs for due diligence and monitoring efforts will take place in the forms of reputable lead arrangers in the syndicate.*

Hypothesis 4B (Experience): *If the loan structure is such that it minimizes probability of default, then the needs for due diligence and monitoring efforts will take place in the forms of experienced lead ar-*

[5]This is but an imperfect way to reduce risk in loans (Lee and Mullineaux, 2004).

rangers in the syndicate.

Our set of loan structure variables include GUARANTEE, a dummy variable that is equal to one if the loan is a guarantee; FINANCIAL COVENANT, a dummy variable that is equal to one if the loan has a financial covenant; LETTER CREDIT is a dummy variable that is equal to one if the loan has a letter credit; and, FEES INDICATOR, a dummy variable that is equal to one if the loan has any fees and zero otherwise. Since lead arrangers have the task of setting the contract of the loan, we expect a positive coefficient in these dummy variables thus implying that reputable and experienced lead arrangers are important in structuring a loan that attempts to mitigate risk.

5.5 Controls

In addition, we control for the size of the loan, which is related with the type of project the loan is financing; and for other types of loans, such as loans to raise capital. The size of the deal is one of the first indications of whether or not the loan has to be syndicated reason being that larger loans may capitally-constrain lead arrangers and participating banks by sharing larger shares of the loan Dennis and Mullineaux (2000). In addition, these remaining types of loans carry risk with them as well, so we should expect a similar result to the hypotheses outlined under credit risk.

6 Data and Summary Statistics

We use Dealscan by Thomson Reuters Loan Pricing Corporation as our only source of data on global corporate loans. This database contains detailed historical information on the entire population of global corporate loans, including syndicated loans, made to medium and large sized U.S. and foreign firms. We use the information on this database to create social network representations of the syndicates formed between 1990 and 2010. In order to create these networks, we need precise information about the lead arrangers involved in each loan. Therefore, we require that the loan observations we use from Dealscan contain both, the lead arranger and number of arrangers, fields populated. If the *Lead Arranger* field is empty and the *Arranger* field is not, then we take the bank listed under the *Arranger* role as the lead arranger of the loan. We validate the number of lead arrangers per loan by calculating the number of commas plus one, in the *Lead Arranger* field when this one is non-empty. Following this methodology, we find that approximately 30% of the deals in the database have multiple lead arrangers. However, the majority of bank loans are arranged by a single lead arranger. Most loans that have more than 1 lead arranger range between 2 and 10 lead arrangers per syndicate. The maximum number of lead arrangers in a loan is found to be 43 in a loan issued in 1991.

Overall, we use data on loan and borrower characteristics in combination with network-derived metrics about syndicate members. Loan characteristics include loan size, maturity, fees, loan purpose, tranche information, and loan type. Borrower characteristics include covenants, size, rating information, type, and information on previous relationships with syndicate members. Network metrics include closeness centrality, and degree.

Table 1 provides the descriptive statistics for the key variables used in our analysis. The data span the period from 1990 to 2010, and includes 193,559 loans. On the average, loan syndicates have 1.73 lead arrangers. The average loan has a maturity of approximately 2.5 years. 40% of all loans charge fees, and 20% of them include convenants. The largest proportion of loans (37%) is used for corporate purposes, followed by M&As and then by repayment-purposed loans. Only 5% of all loans are used for project finance, and a lesser proportion (2%) are used for real estate purposes. 31% of all loans are refinance loans and 13% are term loans. In terms of borrower opacity, only 36% of all borrowers have a rating by Moody's, and 28% are public firms, with manufacturing being the best-represented sector (27%).

Table 1
Descriptive Statistics
This table presents summary statistics for a total of 193,559 corporate loans issued between 1990 and 2010. Summary statistics are calculated at the deal level.

Variable Name	Min	Max	Mean	S.D.
Syndicate Variables:				
Number of Arrangers	1	43	1.730	1.940
Average[Degree]	0	443	79.920	84.520
Max[Closeness]	0	1	0.410	0.160
Loan Variables:				
Log[Deal Amount]	10	24.730	18.610	1.570
Tenor Maturity	0	881	54.030	46.610
Fees (Sum)	0	1437.5	40.150	93.820
Fees Dummy	0	1	0.390	0.490
Fees (Upfront, Commitment and Annual)	0	950	19.790	43.920
Financial Covenant	0	1	0.180	0.380
Loan Purpose:				
Repay	0	1	0.140	0.340
Corporate	0	1	0.370	0.480
Working Capital	0	1	0.110	0.310
Project Finance	0	1	0.050	0.220
LBO	0	1	0.070	0.260
Real Estate	0	1	0.030	0.170
Capital Expenditures	0	1	0.020	0.120
M&A	0	1	0.180	0.380
Other (Purpose)	0	1	0.820	0.380
Loan Type:				
Term Loan	0	1	0.130	0.340
Revolving Credit	0	1	0.060	0.240
Letter Credit	0	1	0.000	0.050
Guarantee	0	1	0.060	0.250
Refinance Loan	0	1	0.310	0.460
Other (Type)	0	1	1.000	0.060
Borrower Variables:				
Rated (Moody)	0	1	0.360	0.480
Log[Borrower Size]	0.690	27.430	19.770	1.950
Multiple Tranches	0	1	0.070	0.260
Previous borrower indicator	0	1	0.430	0.490
Max[Number Loans with Same Lender]	1	158	1.980	4.670
Public Borrower	0	1	0.280	0.450

6.1 Methodology

We examine the relation between syndicate structure, loan characteristics, and borrower opaqueness through a series of regression analyses. In the first regression, we use the syndicate degree as our dependent variable. We measure syndicate degree as the average of undirected links of the lead arrangers in the syndicate. In the second regression, we use syndicate closeness centrality as our dependent variable. We measure syndicate closeness centrality as the maximum closeness centrality measure within the syndicate. While syndicate degree and syndicate closeness centrality are related, they differ in important ways. Syndicate degree measures the extent to which syndicate lead arrangers are active in the global corporate loan market and thus their experience in loan arrangement. Moreover, syndicate degree serves as a proxy for loan arrangement under the assumption that arrangers gain experience through frequent loan arrangements. Closeness centrality measures the extent to which a lead arranger is central within the global corporate loan market. Lead arrangers with a high closeness centrality are closer to any other lead arranger in the network and can be perceived as highly reputable arrangers. Closeness centrality is a monitoring capital variable under the assumption that reputable banks are better monitors and hence their reputation within the market. Overall, closeness centrality allows us to analyze monitoring experience, while syndicate degree allows us to analyze loan arranging experience.

We expect the requirements for arranging loans, to be affected by two factors, loan-level characteristics, and borrower opaqueness. We do so by estimating the following specification:

$$\begin{aligned} Syndicate_i = \alpha + \beta_1 CreditRisk_i + \beta_2 BorrowerInformation_i + \\ \beta_3 ProjectRisk_i + \beta_4 LoanStructure_i + \beta_5 Controls_i + \epsilon \end{aligned}$$

The key independent variables are our measures of loan complexity, borrower opaqueness and market risk. To characterize the complexity of a loan, we use information about its maturity, purpose, type, and fees charged. LOG[DEAL AMOUNT] is the logarithm of the deal amount in U.S. dollars. MULTIPLE TRANCH INDICATOR is equal to one if the deal has multiple tranches and 0 otherwise. TENOR MATURITY is the anticipated time period in which the terms and obligations of the loan must be met between the borrower and lender. This is also an indicator of monitoring capital needs since longer loans require an extended period of borrower monitoring. We identify 8 purposes for a loan, REPAY, CORPORATE, WORKING CAPITAL, PROJECT FINANCE, LBO, REAL ESTATE, CAPITAL EXPENDITURE, and M&A. Therefore, we have 8 loan purpose indicator variables, one for each purpose. They equal one when the deal falls within a certain category. In addition, we identify 4 types of loans, TERM, REVOLVING CREDIT, GUARANTEE, LETTER CREDIT. We also include indicator variables for GUARANTEE LOANS and REFINANCE LOANS. FEES include *annual fees, cancellation fees, commitment fees, documentary issuing fees, documentary LC fees, letter of credit fees, upfront fees*, and *utilization fees*. In addition, we also use FEES INDICATOR which equals 1 if there are any observed fees and 0 otherwise. We also control for loan size.

To characterize the extent to which a borrower is opaque, we classify firms as PUBLIC if they have a ticker on the LPC database. Public firms are expected to require more monitoring and due diligence from the lead arrangers. We identify whether or not the deal has FINANCIAL COVENANTS and use this indicator variable as a measure of borrower opaqueness. Covenants are a form to mitigate information asymmetries with respect to the borrower. Bradley and Roberts (2003) find that smaller firms, firms with higher growth opportunities, and highly levered firms are more likely to have loans with covenants. We measure BORROWER SIZE as the log of its sales. Smaller firms are more opaque than larger firms since public information about them is scarcer than for larger firms. The RATED indicator is equal to one for public borrowers with publicly available accounting with credit quality measured by an independent third party company, in this case Moody's. Information asymmetry between lead arrangers and borrowers is least severe on loans to transparent firms. PREVIOUS BORROWER indicator is equal to one if the borrowing firm has previously obtained a loan with at least one of the syndicate members in the current deal.

With specification 1, we expect, under our null hypotheses, the estimated coefficients to be jointly significantly different from zero for each variable group. The table below summarizes our hypotheses and expected results.

Hypothesis	**Variable Group**	**Expected Results**
Reputation: Max[Closeness Centrality]		
1A	Credit risk	+
2A	Borrower information	+
3A	Project risk	+/-
4A	Loan structure	+
Experience: Avg[Degree]		
1B	Credit risk	+/-
2B	Borrower information	+/-
3B	Project risk	+/-
4B	Loan structure	+

Our estimation for dependent variable DEGREE is estimated with a negative binomial underlying distribution function. CLOSENESS CENTRALITY is estimated using OLS. Our unit of analysis is at the deal level. Both estimations have clustered standard errors at the borrower level.

7 Results

Our first set of hypotheses concern credit risk and how loan syndicates handle that type of risk. On one hand, the credit risk inherited from term, revolving credit and refinance loans is alleviated through better experienced and reputable lead arrangers. On the other hand, however, loans with multiple tranches are not. The alternative explanation for this result is that loans with multiple tranches are relatively riskier than term, revolving and/or refinance loans and hence, experienced lead arrangers do not have sufficient monitoring capacity to arrange multiple tranche loans. In addition, they may pose a risk in their reputation as lead arrangers.

Our second hypothsis deals with borrower information. When the borrower is less opaque, and this information is publicly available, forming a syndicate that can properly monitor is simpler. In general these syndicates do not require high arranging experience or reputation. However, when the information about the borrower is rather of private nature, i.e. obtained through previous collaboration, then more reputable and experienced lead arrangers join the syndicate. This suggests that having access to non-public information provides an incentive to join the syndicate since the due diligence and monitoring efforts in arranging such loan decrease and the reputational returns are higher, especially for reputable lead arrangers. On the other hand, for highly-experienced lead arrangers this means that they are now able to leverage their skills in multiple other syndication projects.

Our third hypothesis relates project risk and syndicate structure. We see that in general, project risk results in less experienced and reputable lead arrangers in the syndicate. This suggests that in the presence of high project risk, a reputable lead arranger prefers not to jeopardize its position by not participating in such deal. Moreover, an experienced and active lead arranger is not able to offer the required monitoring efforts required by such risky loan.

Our last hypothesis is about how a loan is structured to handle potential risks. Overall, as expected we see that when a loan is structured to minimize probability of default or rather to increase the probability of repayment, then the needs for syndication efforts are minimized resulting in syndicates with less reputable and experienced lead arrangers. Structuring a loan in such a way takes care of the much effort that is expected by lead arrangers.

7.1 Syndicate Evolution

In the past 20 years, we have observed changes in the corporate loan market in terms of both, types of loans and syndicate structure. In a larger and more interconnected market, we expect the marginal contribution in terms of reputation and experience by each individual arranger to be smaller in a market where arrangers are better connected and simply co-arrange more loans.

In lieu of the changing loan market, the regression estimates presented in table 3 indicate that despite the underlying changes in the network of lead arrangers, the way in which syndicates are structure has not changed much. Few changes apply, for example, in terms of project risk, now project finance loans rely on having more reputable lead arrangers as opposed to earlier years.

8 Conclusion

In this paper, we explore how information asymmetry about the borrowing firm and loan complexity influence loan arrangement in the global corporate loan market. Our results show that there is indeed a relationship between information asymmetry and the structure of the syndicate issuing the loan. The structure of the syndicate changes depending on whether the loan demands higher monitoring and/or due diligence. In the second part of this paper, we studied how the market has changed and how these changes reflect on syndicate structure. Despite the market evolution and increasing complexity, we observe that syndicates still regard reputation and experience important.

Table 2
Syndicate Structure Regression Results
This table reports coefficient estimates from regressions relating different syndicate structure measures to information about loans, borrower and market opaqueness. Standard errors are presented in brackets.

	Avg[Degree]		Max[Closeness]	
	Estimate	S.E.	Estimate	S.E.
Intercept	-0.1822*	0.0966	-0.2976***	0.0107
Credit Risk				
Multiple Tranche	-0.582***	0.0173	-0.0267***	0.0027
Revolving Credit	0.7611***	0.0156	0.0824***	0.0019
Maturity	0.000	0.0001	0.000	0.000
Term Loan	0.5914***	0.0146	0.0736***	0.0016
Refinance Loan	0.2231***	0.0106	0.0277***	0.0013
Borrower Information				
Public	-0.0529***	0.014	-0.0134***	0.0018
Rated (Moody's)	-0.328***	0.0147	-0.0309***	0.0015
Previous Borrower	0.0359***	0.0091	0.0005	0.0009
Max[# Loans with Syndicate Members]	0.0086**	0.0036	0.0011***	0.0002
Project Risk				
Project Finance	-0.1161***	0.0223	0.0039	0.003
Real Estate	-0.0199	0.0274	0.0051*	0.0031
M&A	-0.1212***	0.0173	-0.0096***	0.0021
Loan Structure				
Guarantee Facility	-0.0753	0.0886	-0.0014	0.0085
Letter Credit	-0.0898	0.0636	0.0113	0.0098
Guarantee Loan	-0.1071***	0.0165	-0.0069***	0.0021
Fees	-0.0004***	0.000	-0.0001***	0.000
Fees (Dummy)	-0.3076***	0.01	-0.0264***	0.0013
Financial Covenants	-0.3036***	0.0127	-0.041***	0.0018
Controls				
Log[Deal Amount]	0.2479***	0.0051	0.0389***	0.0006
Repay Loan	-0.3466***	0.0167	-0.0387***	0.0021
Corporate Purposes	0.0197	0.0138	0.0086***	0.0017
Working Capital	0.1094***	0.0174	0.0072***	0.0022
LBO	0.2187***	0.0215	0.0275***	0.0025
Capital Expenditures	0.0578*	0.0332	0.0081**	0.0041

*, **, *** significant at the 10%, 5% and 1% significance level, respectively. Clustered standard errors.

Table 3
1990-1999, 2000-2010 Syndicate Structure Regression Results
This table reports coefficient estimates from regressions relating different syndicate structure measures to information about loans, borrower and market opaqueness. Standard errors are presented in brackets.

	Avg[Degree]				Max[Closeness]			
	1999		2010		1999		2010	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Intercept	-2.4294***	0.1667	1.56***	0.0836	-0.4074***	0.0202	-0.1144***	0.0103
Log[Deal Amount]	0.3483***	0.0088	0.1535***	0.0045	0.0426***	0.0011	0.0292***	0.0006
Credit Risk								
Multiple Tranche	-0.0853***	0.0218	0.000	0.000	0.0159***	0.003	0.000***	0.000
Revolving Credit	0.145***	0.0506	0.6017***	0.0141	0.0062	0.0074	0.0683***	0.0018
Maturity	-0.0006***	0.0002	0.0005	0.0001***	-0.0001**	0.000	0.0001***	0.000
Term Loan	0.5469***	0.0333	0.4583***	0.0128	0.0551***	0.0047	0.0597***	0.0015
Refinance Loan	0.0254	0.0279	0.0586***	0.0108	-0.0053	0.0043	0.0124***	0.0013
Borrower Information								
Public	-0.1319***	0.0245	-0.012	0.0138	-0.0172***	0.0031	-0.0082***	0.0017
Rated (Moody's)	-0.495***	0.0221	0.0373***	0.014	-0.0227***	0.0027	0.0006	0.0017
Previous Borrower	-0.0086	0.0197	0.0397***	0.0084	-0.0059***	0.0023	0.0024***	0.0008
Max[# Loans with Syndicate Members]	0.0109***	0.0023	0.0041***	0.0037	0.0017	0.0001***	0.0005	0.0002
Project Risk								
Project Finance	-0.1408***	0.0461	-0.0557**	0.0248	-0.0045	0.0064	0.0109***	0.0031
Real Estate	-0.5274***	0.1778	-0.0201	0.0262	-0.0624***	0.0193	0.0056**	0.0029
M&A	-0.2425***	0.0286	-0.0289	0.0196	-0.0166***	0.0042	0.003	0.0022
Loan Structure								
Guarantee Facility	-0.0684	0.1943	-0.1338***	0.0861	-0.0525***	0.0211	0.0001	0.008
Letter Credit	0.1333	0.1179	-0.0982***	0.0636	0.0052	0.0185	0.0181**	0.0087
Guarantee Loan	0.1671***	0.038	-0.1225***	0.0169	0.0064	0.0056	-0.0141***	0.0022
Fees	-0.0011***	0.0001	-0.0002***	0.0001	-0.0001***	0.000	0.000***	0.000
Fees (Dummy)	-0.0003	0.0203	-0.2025***	0.0097	0.003	0.0027	-0.0197***	0.0012
Financial Covenants	0.0395*	0.0246	-0.4954***	0.0146	-0.0278***	0.0033	-0.049***	0.0019
Controls								
Repay Loan	-0.3523***	0.0305	-0.0736***	0.018	-0.0247***	0.0044	-0.0073***	0.0022
Corporate Purposes	-0.1501***	0.0252	0.1115***	0.0144	-0.0038	0.0036	0.0161***	0.0017
Working Capital	-0.5539***	0.0411	0.2333***	0.0171	-0.0423***	0.0053	0.0189***	0.0021
LBO	0.2956***	0.0446	0.1177***	0.0235	0.0445***	0.0059	0.0116***	0.0026
Capital Expenditures	0.0007	0.1213	0.0765***	0.032	-0.0019	0.016	0.0097***	0.0041

*, **, *** significant at the 10%, 5% and 1% significance level, respectively. Clustered standard errors.

A Appendix A: Meta Data

- Borrower Size = log(Borrower Sales Size At Close)
- Multiple Tranche Indicator : is equal to one if the tranche amount is larger than the deal amount, 0 otherwise.
- Loan Purpose: set of indicator variables that are equal to one if Dealscan's field *Specific Purpose* is equal to " Corp. Purposes," "Work. cap.," "Debt Repay.," "LBO," "Real Estate," "Capital expend." For the other set, we use a combination with other fields. To identify if the purpose of the loan is project finance, we do the following, the *Project Finance* field <> "N/A," *Market Segment Broad Market Segment* should be equal to "Project Finance" or *Specific Instrument* should be equal to "Project Finance." To identify M&A purpose loans, we search for *Market Segment Broad Market Segment* to equal "M&A" or *Specific Purpose* to equal "Aquis. line" or "Merger" or "Takeover." Purpose "other" is equal to one for all other purposes not listed here. These categories, except "Other" alone account for about 90% of all purpose loans. Corporate purposes is the largest classification with about 40% of all loans falling in this category.
- Public indicator: equal to one if *Borrower Parent Ticker* is not equal to "N/A"
- Financial covenant indicator: equal to one if *Covenants Financial Covenants Y* is equal to "Yes" 0 otherwise.
- General covenant indicator: is equal to one if *Covenants General All Covenants* is not equal to "N/A"
- Secured: equal to one if *Secured Unsecured* field equals "Secured"
- Rated moody: is equal to 1 if *Ratings Mooddy s Senior Debt at C* <> "NR", 0 otherwise.
- Rated close: is equal to 1 if *Ratings All At Close* <> "N/A"
- Loan type: set of indicator variables including *Term Loan, Revolving Credit, Guarantee, Letter Credit, Long Term, Other*.

B Appendix B

Table 4
Top Lead Arrangers by Network Metric
This table lists the top 10 lead arrangers by network metric in the sample of banks in 2010. The first column contains the top 10 banks in terms of their clustering coefficient. The second column lists the top 10 banks in terms of their degree measure. The third column lists the top 10 banks in terms of their closeness centrality and the fourth column lists the top 10 banks in terms of their betweenness centrality.

(1) Clustering Coefficient		(2) Degree		(3) Closeness Centrality		(4) Betweenness Centrality	
MPS Capital Services	1	BNP Paribas	443	Bank of China	1	Credit Agricole Corporate	0.074
China Merchants Bank Shanghai	1	Credit Agricole Corporate Investment Bank SA	421	ICBC	1	BNP Paribas	0.067
Czech Export Bank	1	Bank of Tokyo-Mitsubishi UFJ Ltd	365	HSBC Bank (China)	1	Bank of Tokyo-Mitsubishi UFJ Ltd	0.056
KFW International Finance Inc	1	HSBC	360	Innovation Capital LLC	1	Standard Chartered Bank Plc	0.056
Bank of Tokyo–Mitsubishi UFJ Ltd	1	Royal Bank of Scotland PLC	347	HCB Bank Ltd	1	HSBC	0.049
Macquarie Securitisation Ltd	1	Deutsche Bank AG	338	Standard Chartered Bank (Pakistan) Ltd.	1	Royal Bank of Scotland PLC	0.043
Mizuho Corporate Australia	1	Standard Chartered Bank Plc	319	National Bank of Oman	1	Bank of America Merrill Lynch	0.035
Danish Ship Finance	1	Natixis SA	310	PNB Capital	1	DBS Bank Ltd	0.032
Taiwan Cooperative Bank	1	Bank of America Merrill Lynch	295	First Metro Investment Corp	1	Natixis SA	0.032
Far Eastern Commercial Bank	1	Barclays Bank Plc	284	RHB Islamic Bank	1	Deutsche Bank AG	0.031

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