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# Lending when relationships are scarce: The role of information spread via bank networks

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A B S T R A C T

We investigate how information flows within bank networks facilitate syndicate formation and lending in the leveraged buyout (LBO) market, where relationships between banks and borrowers are scarce and borrower opacity is high. Using novel measures that characterize a bank's ability to source and disseminate information within its loan syndication network, we show that the extent of this capability influences which banks join the syndicate, the share the lead bank holds, and LBO borrowing terms. Banks' ability to source and disseminate network-based information is particularly useful when ties to prospective borrowers are lacking, with the information flows extending beyond knowledge on PE firms and LBO targets.

## 1. Introduction

A large body of research has investigated the benefits to banks of building close ties with borrowers. Using the duration and intensity of borrowing as proxies for lending relationships, this literature documents that strong ties reduce information asymmetries between banks and borrowers (Boot, 2000 Diamond, 1984 Farinha and Santos, 2002 Rajan, 1992 Sharpe, 1990), thereby improving credit access (Petersen and Rajan, 1994, 1995), reducing the cost of debt (Berger and Udell, 1995 Bolton et al., 2016 Ivashina and Kovner, 2011 López-Espinosa et al., 2017), and lowering collateral requirements (Degryse and Van Cayseele, 2000).

While these studies showcase the benefits of relationship lending to both banks and borrowers, lending relationships are often scarce and difficult to establish in settings characterized by acute information asymmetries. One such important setting is the market for leveraged buyouts (LBOs) where a private equity (PE) firm uses mainly debt to acquire a "target" company.[1] The majority of LBO targets are private firms whose creditworthiness is hard to evaluate compared to publicly listed peers. Given that the median LBO in

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[1] Typically, PE firms use debt to finance between 60 and 90% of the LBO (Gompers et al., 2016; Kaplan and Strömberg, 2009). Global LBO deal volume was $551 billion in 2019, with the US accounting for 41% of all LBO deals in that year (Bain and Company, 2020).

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our data carries a debt load exceeding $200 million and 5 years in loan maturity, it follows that the banks funding these deals are exposed to substantial credit risks (about $50 million per bank in a syndicate on average).

Theory suggests that banks adopt two main strategies to deal with this important risk exposure. First, two or more banks might form a "syndicate" to share risks and jointly issue the LBO loan (Sufi, 2007). Second, banks will lend mostly to borrowers with whom they share strong ties to reduce risk and uncertainty (Ivashina and Kovner, 2011). In practice, while the syndication of LBO loans is widespread, our data shows that PE firms and targets do not have ties to banks in the LBO loan syndicate in at least 48% of the deals in our sample.[2] Given that relationship lending is an important mechanism for mitigating information frictions during the lending process (Fang et al., 2013 Ivashina and Kovner, 2011 Sufi, 2007), the absence of ties implies that banks use other channels to access the requisite information.

This paper provides new evidence on one such channel – the bank syndication network – as a source of information during LBO loan origination. Understanding how a bank network functions and affects loan syndication and provision is an important, and relatively unexplored, question in finance. Existing work has focused mainly on network proxies of bank reputation and experience, such as its *Degree* and *Eigenvector*, to explain benefits in terms of reduction of information asymmetry and loan raising (Godlewski and Sanditov, 2017 Godlewski et al., 2012). However, these and other traditional and widely used proxies are unsuited to capture the mechanisms of information propagation through the network.[3]

We exploit recent advances in social network research to make significant progress on the above challenges. Specifically, we employ two recently developed centrality measures, *Diffusion* and *Sourcing*, to capture a bank's capability to source information from the loan syndication network as well as to provide information to it. These measures were first introduced by Banerjee et al. (2013), and later refined by Banerjee et al. (2019), to understand information flows within village community networks.[4] Our measures assume that information is passed stochastically from one node to another in the network with a fixed per-period transmission probability.[5] *Diffusion* of a given bank measures the expected total number of times that any other bank in the network receives information broadcasted by this bank. *Sourcing* captures how often a given bank might expect to hear from every other bank in the network. Intuitively, *Diffusion* informs about the extent to which information spreads out from a given bank or, in other words, the bank's ability to send information within the network. *Sourcing*, on the other hand, informs about the extent to which a bank can be informed by other banks in the network. We refer to these jointly as *information centralities*.

Our analysis uses a sample of 2414 LBO loans issued in the US between 1986 and 2012. This data is sourced mainly from Reuters' LPC DealScan, a database used by many previous studies on syndicated loans (Bharath et al., 2011 Demiroglu and James, 2010 Fang et al., 2013 Fernando et al., 2012 Ivashina, 2009 Ivashina and Kovner, 2011 Sufi, 2007).[6]

We begin by showing that banks' information centralities are distinct from traditional centralities that are proxying bank reputation, like *Degree* and *Eigenvector* (Godlewski and Sanditov, 2017 Godlewski et al., 2012).[7] Next, we estimate the effects of network centralities on the loan syndication process, which begins after the LBO borrowers appoint a *lead bank* to *arrange* the loan. The lead bank attempts to sell portions of the loan by inviting other banks and financial institutions within its network (Ivashina, 2009). Interested banks join the syndicate and contribute their agreed shares to the loan. Once the syndicate is formed and the required loan

[2] Henceforth we collectively refer to PE firms and LBO targets as "borrowers" or "LBO borrowers". Our analysis shows that lead banks do not have pre-existing ties with the sponsoring PE firm (target) in 48% (79%) of the LBO deals in our sample. Similarly, non-lead banks in the syndicate do not have ties with the sponsoring PE firm (target) in 72% (89%) of the LBO deals in our sample.

[3] Godlewski et al. (2012) and Godlewski and Sanditov (2017) use centrality measures based on network topology as proxies for bank reputation, and argue that better-connected banks have more reputation and are more informed, which helps them mitigate lending costs. However, the causal link between network topology and information access is unclear. By their very design, centralities based only on the network topology cannot inform about how information actually propagates through the network. Recent work in sociology indeed shows that reputed actors do not always diffuse more information into the network (Duarte et al., 2019).

[4] Banerjee et al. (2013) and Banerjee et al. (2019) denote these as *Diffusion* centrality and *Gossip* centrality, respectively. Although village networks are built on informal ties among residents, information flows in these networks are non-random and influenced by endogenous social and demographic factors like proximity, wealth status, occupation, religion, and caste (Dercon, 2005; Udry and Conley, 2004). While *Diffusion* and *Sourcing* were developed to study such *informal* village networks, the similarity of information dynamics in more formal settings provides a key motivation for this paper's use of *Diffusion* and *Sourcing* to study information flows within bank syndication networks.

[5] This assumption is required because actual information flows between banks are not observable. However, Banerjee et al. (2019) show that the assumption of a fixed per-period information transmission probability does not affect the correct relative ranking of network nodes (banks) as a function of their *Diffusion* and *Sourcing* centralities in the network.

[6] This paper focuses only on LBO loans rather than the entire corporate syndicated loan market for many reasons. First, the mean LBO loan is five times larger than the typical corporate loan, meaning that banks issuing LBO loans must contend with higher credit exposure and uncertainty. Second, over 91% of LBO targets are private firms that present significant adverse selection challenges to investing banks. This means that gathering and sharing of information among banks, including through their networks, is crucial during syndication. Such issues are less likely in the case of syndicated loans issued for other purposes like capital expenditures or working capital. Third, LBOs involve transfer of ownership to the acquiring PE firm with the target undergoing significant reorganization post LBO (Bernstein and Sheen, 2016; Davis et al., 2019). The lending syndicate must evaluate the unique moral hazard challenges due to such changes (Gompers et al., 2016), which do not exist for other loans. Lastly, PE firms are repeat players in the LBO market and tend to establish ties with banks (Ivashina and Kovner, 2011), which are less prevalent for borrowers of other loans. Focusing on the LBO market allows us to better identify whether the information spread via bank networks matters despite the presence of these ties.

[7] The literature has also used other centrality measures, like for example *Betweenness* and *Katz-Bonacich* centralities. Given the high correlation between the latter and both the *Degree* and *Eigenvector*, and for the sake of conciseness, we only focus on the *Degree* and *Eigenvector* in the paper.

amount raised, the lead bank negotiates lending terms such as maturity, collateral, and interest rate with borrowers (Bruche et al., 2020). Fig. 1 presents an overview of these steps.

Identifying how information flows within bank networks is empirically challenging for several reasons. First, networks are formed endogenously, and it is difficult to observe communication among banks and quantify how they affect loan syndication decisions. Second, LPC reports only completed loans, and does not provide data on banks that were invited to join a syndicate but did not eventually do so. This makes it difficult to observe banks' detailed actions and identify clear, unambiguous counterfactual decisions. Third, LBO loan syndication is unlikely to be random, and omitted factors could affect both bank-level information sharing and lending decisions, making it difficult to infer a causal relationship.

We address the above identification problems by developing suitable counterfactuals for realized syndication decisions using propensity score (PS) matching, wherein incumbent syndicate *members* are matched to ten other banks that did not actually join, but otherwise have similar characteristics. We refer to these collectively as the *candidate* banks. As participation in a syndicate is dichotomous for each of the candidate banks, we use conditional logit (CL) models to obtain consistent estimates from this matched sample and correct for unobservable heterogeneity at the deal level. To allay concerns of reverse causality, we use lags of centrality measures relative to the timing of a focal deal. This approach allows us to control for the endogeneity of potential differences in the LBO loan syndication process across less- and better-connected banks.

Controlling for prior ties and geographic distances between lead and candidate banks, and between candidate banks and borrowers, our CL estimates show that *Diffusion* and *Sourcing* have a substantial and positive impact on the odds that a candidate bank joins an LBO syndicate. Specifically, a one-standard-deviation increase in *Diffusion* (*Sourcing*) leads to a 41.5% (83.9%) rise in a candidate's odds of joining the syndicate. Thus, the more a candidate bank is expected to hear from the network (*Sourcing)*, and the more it is plausibly informed, the greater is its probability to join the syndicate. Similarly, syndicates are more likely to include partners from which the lead banks have heard more frequently, as captured by the candidates' *Diffusion*.

If information that reaches banks through networks is so crucial during LBO syndication, a natural question is whether banks continue to rely on the network for information if they already know the borrowers or have worked with the syndicate banks in prior interactions. To answer this, we interact *Sourcing* with relationship proxies between candidate banks and borrowers. The corresponding CL estimates suggest that, when a candidate bank lacks prior ties to incumbent borrowers, information that could be sourced by a candidate bank from the network is instrumental to it joining the syndicate; the probability to join almost doubles as one moves from the 5th to 95th percentile for *Sourcing*. When a candidate bank has prior ties to incumbent borrowers, the probability of joining a syndicate also increases with the strength of *Sourcing*. However, the marginal effect of *Sourcing* on syndicate joining conditional on the candidate's ties to PE sponsors is stronger than its effect conditional on the candidate's ties to LBO targets. *Diffusion* exhibits similar behavior when it comes to syndicate joining. Taken together these analyses suggest that while having prior ties is always beneficial for the candidate banks' probability to join LBO syndicates, information centralities complement lending relationships in this setting.

Next, we investigate how the information centralities of the lead bank might affect its share of the LBO loan upon syndicate formation. This question is important since candidates will assess the need for ex-ante due diligence and ex-post monitoring of the borrower, and ascertain the lead bank's incentives to offer bad loans or shirk monitoring duties (Bharath et al., 2011 Ivashina, 2009 Sufi, 2007). Conditional on prior ties, if participating banks cannot acquire information relevant to the lead bank and borrowers from the network, they might try to minimize credit exposure and force the lead bank to hold a greater part of the loan. Similarly, the extent to which the lead bank can acquire information relevant to candidates and borrowers from the network might impact how much of the LBO loan it sells to incoming participants. Since our data does not allow us to capture actual information flows through the network, we interpret the observed lead bank share as an equilibrium outcome resulting from the overall information processed by lead and participant banks.

We use fractional response models to estimate the effects of network centralities on *lead bank share*, which ranges between zero and one.[8] Coefficients of lead bank *Diffusion* and *Sourcing* are negative and highly significant at the 1% level. A one-standard-deviation increase in lead bank *Diffusion* (*Sourcing*) leads to a 3.1% (2.6%) drop in the LBO loan share from the mean of 41.9%. This implies that lead banks that source (disseminate) more information from (into) the network manage to sell a greater share of the loan.[9]

Lastly, we assess whether information centralities impact LBO loan terms, comprising loan maturity, collateral requirements, and interest rate. We follow Melnik and Plaut (1986) and Dennis et al. (2000), and model LBO loans as *n*-dimensional contracts, where each dimension denotes a specific loan term that is set jointly with the other terms. We use a system of equations to model loan maturity and collateral jointly, and then model loan spread as being determined jointly by these two terms. To resolve the endogeneity problem associated with the joint determination of loan terms, we follow Bharath et al. (2011) and use instrumental variables two-stage least squares (2SLS) regressions to analyze each equation.

Our findings suggest that a one-standard-deviation increase in lead bank *Diffusion* corresponds to a 0.11 standard deviation increase

[8] Since *lead bank share* is determined after the syndicate has been formed, we no longer require the PS matched sample, and instead use deal level data for the remaining analysis.

[9] Besides controlling for bank-borrower ties and deal characteristics, we include cross-sectional reputation of the sponsoring PE firm as a proxy for target firm opacity. This proxy is included to account for the fact that reputation signals selection and monitoring skills of the PE firm (Demiroglu and James, 2010), and also because reputed PE firms tend to be more conservative and less risk-taking (Gompers et al., 2016). LBOs by reputed PE firms should thus require less due diligence and be easier to syndicate. Our findings show that better reputation combined with a greater ability to source network information make it easier to assess and monitor the target. In such cases, lead banks find it easier to sell more of the LBO loan to syndicate members.

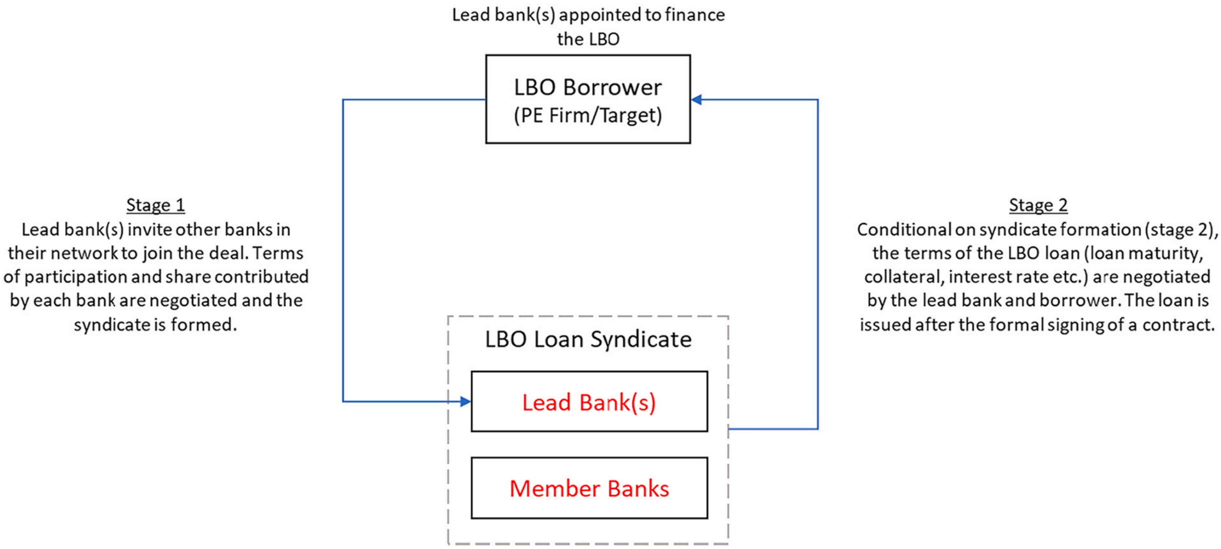


**Fig. 1.** LBO loan syndication process.
The loan syndication process for a leveraged buyout (LBO) typically begins after a lead bank (or a group of lead banks in some cases) is chosen to arrange a loan for the deal. Subsequently, the lead bank solicits other banks in its network to sell parts of the loan to them. During this process, the lead bank collects information on the borrowers (i.e. LBO target and PE firm) and conducts due diligence. Based on its assessment, the lead bank submits a confidential memorandum to prospective syndicate members (participants), containing details of borrowers and an assessement of the deal. Interested banks will negotiate the terms of their participation and sign letters of commitment with the lead bank. Upon forming the syndicate, the lead bank negotiates the terms of the LBO loan package (such as loan maturity, collateral requirements, and interest rate) with the borrowers. Post syndication, the lead bank is responsible for monitoring the borrowers and communicating their performance to the members. Thus, the lead bank acts as an agent on behalf of the lending syndicate. For a detailed description of the loan syndication process, see Altunbaş et al. (2006), Sufi (2007), Ivashina (2009), and, Bharath et al. (2011).

in loan maturity (equivalent to 1.2 months increase) for the mean LBO with a maturity of 66.8 months. Similarly, while half of the deals require collateral, a one-standard-deviation increase in lead bank *Diffusion* (*Sourcing*) lowers the probability of collateral demand by up to 16% (13%). Lastly, a one-standard-deviation increase in lead bank *Diffusion* (*Sourcing*) lowers the mean interest rate spread (over LIBOR) of 3.8% by 13 (11) basis points. In economic terms, the discounted cash saved from lower interest rates due to lead bank *Diffusion* is $1.2 million over the mean loan period, implying a 0.6% higher return for every dollar invested by the PE firm. These results are consistent with the idea that information diffusion and sourcing capabilities by lead banks enable LBO loan issuance on cheaper terms.[10]

Our paper contributes to several strands of literature. First, recent studies explored the role social networks play in financial markets. For instance, Bajo et al. (2016) find that more central investment banks enjoy pricing advantages for their IPOs. Plagmann and Lutz (2019) show that more central VC firms attract higher quality peers as syndicate partners, while Hochberg et al. (2007) show that funds of better networked VCs perform better. Li and Schürhoff (2019) show that more central bond dealers levy higher trading costs but provide faster execution. Two relevant studies on loan syndication by Godlewski et al. (2012) and Godlewski and Sanditov (2017) use traditional centralities to argue that better-connected banks enjoy reputational advantages that help them mitigate lending costs. A common assumption in all these studies is that actors are fully aware of their network. We add to this literature by showing how banks learn from each other by sharing information via the network despite being unaware of its entire topology.

Second, our paper adds to the literature on syndication and partner selection decisions in financial markets. Studies show that investors syndicate to diversify their risks by co-investing (Ivashina and Scharfstein, 2010 Lerner, 1994). Ties built on repeat syndication create networks that facilitate both direct and indirect exchange of information among investors (Hochberg et al., 2015). "Central" investors within such networks have better knowledge of opportunities and competition (Hochberg et al., 2007 Sorenson and Stuart, 2001 Sufi, 2007), and have a reputation for being successful, all of which has a certification effect on the firms that they invest in (Ozmel et al., 2013 Robinson and Stuart, 2007). We complement this literature by showing that loan syndication depends on connections and information exchange among banks, without which they will be unable to diversify the risks present in their individual loan portfolios.

The rest of the paper is organized as follows. Section 2 describes the information and traditional centrality measures. Section 3 presents the sample and summary statistics. Section 4 describes the empirical design and results. Finally, Section 5 concludes.

[10] In comparison, coefficients of topological centralities are only significant up to the 10% level for all loan terms. This implies that network position is a weaker mechanism to resolve information asymmetries compared to information centralities.

## 2. Research framework

Our analysis focuses on the network of banks active in the syndicated US LBO loan market. Accordingly, we begin by describing the structure of this network. We then introduce network centrality measures that characterize the extent to which banks are expected to transmit information. These measures, denoted *Diffusion* and *Sourcing*, capture a bank's ability to diffuse and source information from its loan syndication network. In addition, we also consider two traditional *Centralities* – *Degree* and *Eigenvector* – in our analysis. Finally, we describe the type of information that banks plausibly exchange via this network.

### 2.1. Network structure

We determine the structure of the LBO loan syndication network based on the interactions between constituent banks. This structure is then used to estimate centralities that characterize each bank's relative position within the network. Our procedure is consistent with prior studies that have used social network analysis (SNA) techniques to understand venture capital (VC) syndication and performance (Hochberg et al., 2007, 2010), underwriting of initial public offerings (IPOs) (Bajo et al., 2016), corporate finance policies (Fracassi, 2017), interbank lending (Kobayashi and Takaguchi, 2018), over-the-counter trading (Li and Schürhoff, 2019), and bilateral trade between countries (Richmond, 2019).

We define two banks *i* and *j* as having a tie (i.e., a prior interaction) in year *t* if they were part of at least one LBO loan syndicate in the past five years.[11] The collection of all such ties constitutes the prevailing syndication network, which can be represented as an *adjacency matrix*.[12] For example, an adjacency matrix representing the bank network for the year 2010 is computed using data on syndicated LBO loans issued between 2005 and 2009. Since the network evolves constantly due to changes in the loan syndication process, market trends, and the entry/exit of banks, we construct adjacency matrices on an annual rolling basis using five-year trailing windows.[13] Our matrices are *undirected* (and thus symmetric), with each cell representing the number of past syndicates in which banks *i* and *j* were together. These adjacency matrices are then used to compute the relevant network centralities at the bank-year level. Banks that were not active in the market during a given five-year trailing period are considered "newcomers" if they were part of an LBO in the focal year, and consequently have their network centralities set to zero.

### 2.2. Centrality measures

#### 2.2.1. Diffusion

Our first network measure is *Diffusion* centrality, which captures how information spreads from a given node through the network over a certain number of time periods. *Diffusion* is similar to contagion, and occurs because information generated at one node is passed on stochastically from neighbor to neighbor, along with details of the node that generated that information (Banerjee et al., 2019). More formally, assume some information (e.g., pertaining to an LBO deal or to market conditions at the time of the deal) is initiated at bank *i*, and is broadcasted in the first period $t = 1$ among *i*'s neighbors with probability *p*. During each subsequent period, every informed neighbor shares *this information and the identity of the source* with its neighbors with the same probability *p*. This process is repeated over *T* time periods. The hearing matrix **H** is then defined as:

$$\mathbf{H}(\boldsymbol{g}_y, p, T) = \sum_{t=1}^{T} (p\boldsymbol{g}_y)^t \tag{1}$$

where $\boldsymbol{g}_y$ is the $N \times N$ undirected adjacency matrix of the bank network for a given year *y*. The *ij*-th element of **H** is the expected number of times that bank *j* hears some information that originated from bank *i* over *T* previous periods. Banerjee et al. (2013) show that the per-period transmission probability, *p*, can be reasonably well approximated by $1/\mathrm{E}[\lambda_1(\mathbf{g})]$,which is the inverse of the largest eigenvalue of the adjacency matrix **g**. They also suggest that *T* can be approximated by the diameter of the network. *Diffusion* centrality is thus defined as:

$$\mathit{Diffusion}(\boldsymbol{g}_y, \mathrm{p}, \mathrm{T}) = \mathbf{H}(\boldsymbol{g}_y, \mathrm{p}, \mathrm{T}) \cdot \mathbf{1} = \sum_{t=1}^{T} (p\boldsymbol{g}_y)^t \cdot \mathbf{1} \tag{2}$$

where **1** is a $N \times 1$ column vector of ones. For a given year *y*, $\mathit{Diffusion}_{iy}$ is the expected number of times that information originated by bank *i* is heard by any other member of the network over the time period *T*.[14]

[11] This approach is similar to the manner in which previous studies such as Hochberg et al. (2007), Godlewski et al. (2012), and Bajo et al. (2016) have constructed network-based centrality measures.

[12] Formally, a network of *N* distinct banks forms a $\mathrm{N} \times \mathrm{N}$ matrix $\mathbf{g} = f(i, j)$, where each element $f(i, j)$ denotes a tie between banks *i* and *j*, and function *f* defines the weight of the tie.

[13] To test the robustness of our definition, we re-ran all our analyses with ties measured over shorter time windows. Our results remain consistent to changes in the length of the trailing windows.

[14] Note that the dimension of **H** is the same as that of **g**. Since *p* is a scalar, and **g** is a matrix of $(N \times N)$, $\mathbf{w} = p\mathbf{g}$, is of $(N \times N)$. Any power of **w** is $(N \times N)$, hence the final matrix **H** is of $(N \times N)$. Multiplying **H** by **1** $(N \times 1)$ gives the column vector of $(N \times 1)$, where each row represents the *Diffusion* of the bank in the $i^{th}$ row.

The approximation of $p$ by $1/\lambda_1(\mathbf{g})$ is an important design choice, as explained in Banerjee et al. (2019). If $p$ is small ($\lambda_1(\mathbf{g}) > 1$), then very little information gets diffused over several time periods $T$, meaning that bank $i$ transmits very little information onto the network. Hence its *Diffusion* is low. On the other hand, when $p$ is large ($\lambda_1(\mathbf{g}) < 1$), information can spread quickly and saturate the network, hence bank $i$'s *Diffusion* is high. Banerjee et al. (2019) recommend $p = 1/\lambda_1(\mathbf{g})$ as the optimal threshold at which information may diffuse to all nodes but does not get duplicated. A similar argument applies for using the network diameter $diam(\mathbf{g})$ as a proxy for $T$. When $T < diam(\mathbf{g})$, information from one node does not have enough time to reach all the other nodes. Alternatively, there is saturation if $T > diam(\mathbf{g})$ as information can reach some nodes multiple times as "echoes". Thus, Banerjee et al. (2019) recommend using $T = E[diam(\mathbf{g})]$ as information can diffuse but not necessarily duplicate across the network at this value.[15]

The interpretation of *Diffusion* in subsequent analyses is as follows. From a lead bank's perspective, higher (lower) *Diffusion* of a candidate bank implies that the former expects to receive more (less) information from the latter. Conversely, from a candidate bank's perspective, a lead bank with higher (lower) *Diffusion* is expected to share more (less) information. The nature of information that could be exchanged is discussed in Section 2.3 below. One would therefore expect a greater probability of syndication with banks having higher *Diffusion*.

### 2.2.2. Sourcing

*Diffusion* centrality considers information diffusion from the *sender's* standpoint. To consider how information reaches *receivers* in the network through this diffusion process, we once again follow Banerjee et al. (2019) and use the hearing matrix $\mathbf{H}$ to compute *Sourcing* centrality. *Sourcing* represents how often a given bank $j$ "hears" information from the other banks over $T$ periods. Recall that in each period, a bank receives information originating from various parts of the network. Since $\mathbf{H}(g_y, p, T)_{ij}$ is the expected number of times bank $j$ hears information originating from bank $i$, the $j$-th column of $\mathbf{H}$ denotes bank $j$'s expected information sourcing from every other bank in the network. *Sourcing* centrality of bank $j$ is then estimated as the average of the $j$-th column of $\mathbf{H}$. It is the mean expected number of times a bank hears (receives) information from the entire network. Higher *Sourcing* therefore implies that a bank is particularly well informed not only through its direct ties to other banks, but also through the indirect ties it has with other banks within the syndication network.

### 2.2.3. Degree

*Degree* centrality is the most widely used network measure and is the number of ties an actor has with other members of the network. The intuition behind *Degree* centrality, in the context of LBOs, is that better connected banks have more reputation than less connected peers. Given the adjacency matrix $\mathbf{g}$ of ties among banks over a five-year trailing period, the *Degree* centrality of bank $i$ in year $y$ is defined as:

$$Degree_i = \sum_{j, i \neq j} x_{ij} \tag{3}$$

where $j$ represents all banks excluding $i$. Thus, *Degree* is the sum of row (or column) $i$ of the adjacency matrix $\mathbf{g}$. As $\mathbf{g}$ is computed over a five-year trailing period, $Degree_i$ is essentially the total number of interactions of bank $i$ with LBO syndicate partners during the last five years.

*Degree* grows with network size as bigger networks have a greater pool of connected actors. This introduces a potential bias since bank networks evolve continuously, both in size and composition, making it difficult to use a single network or compare networks across time. Therefore, we normalize *Degree* by the maximum number of ties possible in an $n$-actor network (i.e., $n - 1$).

### 2.2.4. Eigenvector

Although *Degree* captures ties between actors, it does not consider the quality of these ties. Specifically, *Degree* cannot distinguish between two focal banks in which one is connected to a group of banks that are not well-connected, while the other is connected to the same number of banks that are well-connected. While both banks have the same *Degree*, their influence within the network differs with the connectedness of their partner banks.

Consequently, banks having ties to better-connected banks will exert greater influence than those tied to weakly-connected banks. To capture these complexities, we use *Eigenvector* centrality.[16] *Eigenvector* is a specialized variant of *Degree* centrality in which each tie of a given bank is weighted by the respective centrality of that connection. Thus, *Eigenvector* considers the number of connections as well as the centrality of each such connection and captures the extent to which the bank has ties to prominent and well-connected banks in the network. Formally, it is defined as:

$$Eigenvector_i = a \sum\nolimits_{j=1}^{N} x_{ij} e_j \tag{4}$$

[15] The true values of $p$ and $T$ are unobservable to us. In unreported results, available upon request, we also run extensive simulations to understand the behavior of *Diffusion* and *Sourcing* further the changes in the underlying assumptions about $p$ and $T$. Based on the arguments of Banerjee et al. (2013) and Banerjee et al. (2019), and our own simulations, we are confident that our inability to observe the true values of $p$ and $T$ does not inhibit the econometric conclusions of our main analyses.

[16] Given that we use undirected (and thus) symmetric adjacency matrices, *Eigenvector* centrality is also equivalent to the Katz-Bonacich centrality (see Bonacich and Lloyd (2001) for details). We have verified this equivalence in unreported robustness checks.

where $a$ is a constant parameter representing the biggest eigenvector of the corresponding adjacency matrix, and $e_j$ is the eigenvector centrality of bank $j$. To control for potential biases and ensure cross-comparability, we normalize this measure by the highest possible *Eigenvector* in a network of $n$ actors.

### 2.3. Types of information travelling through the network

Although we do not directly observe the information flowing through the LBO loan syndication network, we can nonetheless provide some intuition on the kind of information exchanged over the network that would be instrumental during LBO loan syndication. First, banks may exchange information pertaining to the LBO deals currently under consideration. This can for example include private information on borrowers obtained from prior lending relationships or from other banks through the network. Second, lead banks may invite banks to join their LBO loan syndicate because the latter might share information on and to other banks that might be interested to join the syndicate. Third, interacting with informed banks could help lead banks keep track of latest developments in the syndicated loan market much more precisely compared to what they would be able to learn by simply accessing commercially available databases. This might include information on the buyout market regarding deal valuations, liquidity, loan terms and other conditions. Such information might directly impact loan terms and is otherwise hard to obtain from other sources.

## 3. Data and summary statistics

The primary data source on LBO loans is the Loan Pricing Corporation's (LPC) Dealscan database from Thomson Reuters. LPC data has been widely used in previous studies on loan syndication, particularly those related to LBOs (Bharath et al., 2011 Demiroglu and James, 2010 Fang et al., 2013 Fernando et al., 2012 Ivashina and Kovner, 2011 Sufi, 2007). We complement this transaction-level data with additional information on PE characteristics, such as age and funds raised, from Thomson One (formerly Venture Economics). Information on the pre-LBO characteristics of target firms are available only if they were listed prior to the LBO and are obtained from Compustat. Loan data from LPC contains details of contributions made by lead arrangers and participants at the *tranche* level. Several such tranches, ranked in order of seniority, make up the overall debt package issued to finance an LBO.

Our initial sample consists of 65,362 syndicated loan tranches for 5631 LBO transactions over the period 1986–2012. This data contains deal-specific information such as loan terms, identities of the participating banks, PE firms, and targets, and their observable characteristics. To eliminate heterogeneity of the institutional context, we restrict our sample to US-based LBO targets that were sponsored by US-based PE firms. However, we do not impose any such restrictions on banks and include LBOs arranged or funded by non-US banks. These restrictions result in a final sample of 2414 LBOs comprising 5766 individual loan tranches.[17] The definitions of all our variables are summarized in Table 1.

### 3.1. Summary statistics

Table 2 presents summary statistics on the bank centralities.[18] The mean *Diffusion* centrality of lead banks is nearly 2.5 times higher, on average, than that of members, suggesting that banks that are better at disseminating information may be preferred to form and lead loan syndicates. However, the *Sourcing* centrality of members is slightly higher than that of lead banks, with the $t$-test of the difference in their means statistically significant at 1% level. Lead banks also occupy more central network positions compared to syndicate members, as suggested by the higher *Degree* and *Eigenvector* centralities.[19]

Table 3 shows that *Diffusion* and *Sourcing* are only weakly correlated. This is expected since although both measures are derived from the same hearing matrix **H**, they represent different concepts. *Diffusion* tracks a bank's ability to *send* information into the syndication network whereas *Sourcing* tracks its ability to *receive* information from the same network. *Diffusion* is moderately correlated with *Degree* and *Eigenvector*, which is expected since diffusion centrality is proportional to *Degree* centrality for $T = 1$ and converges to eigenvector centrality when $\lambda_1(\mathbf{g}) > 1$ and $T \rightarrow \infty$ (Banerjee et al., 2013, 2019). *Sourcing* is also partially correlated with *Eigenvector*, which shows that even with little intuition of the network structure, banks can still assess the correct topological ranking among members based on how often they hear about them over sufficient time periods. Lastly, *Degree* and *Eigenvector* are highly correlated with each other, implying considerable overlap between these traditional measures.

Summary statistics on the LBO sample are presented in Table 4. The mean (median) LBO loan package is about \$303 (\$207) million in size, has a maturity of 67 months and carries a spread of 3.8% above LIBOR, suggesting that LBO loans are substantially larger than standard business loans.[20] The median syndicate size, including lead banks, is four. One out of every two LBO loans is secured with collateral, suggesting the high level of perceived riskiness in these deals. Nearly 70% of deals were arranged by domestic banks.

Looking further at bank characteristics reveals that on average lead banks have stronger ties with PE firms than with targets prior to an LBO. Member bank ties with PE firms and targets exhibit a similar pattern but are marginally weaker than lead bank ties. The

[17] Note that a bank can participate in multiple loan tranches within an LBO debt package. However, we count each participating bank only once for an LBO.

[18] All centralities are standardized in the empirical analyses to ensure cross-comparability.

[19] See online Appendix A for pairwise correlations between *Diffusion* and *Sourcing* centralities of lead and syndicate member banks.

[20] Daniels and Morgan (2010) provide evidence that LBO loans are larger in deal size, carry higher interest rates, and are significantly more levered than any other type of corporate syndicated loans.

**Table 1**
Variable definitions.

| Variable | Definition |
|---|---|
| ***LBO loan characteristics*** | |
| Match (D) | Dummy equal to one if a candidate bank joins as a non-lead member in an LBO loan syndicate. |
| Spread (%) | Loan spread in percentage points, weighted by the value of each loan tranche relative to the total deal size. Spreads represent the total interest rate (including fees) paid in excess of LIBOR on the loan package. We use a value-weighted measure of spread since LBO deals typically comprise several loan tranches in an increasing order of seniority, with each tranche having different borrowing terms and characteristics. |
| Maturity | Loan maturity in months, weighted by the value of each loan tranche relative to the total deal size. |
| Collateral | Dummy term equal one if the LBO loan has any collateral requirements. |
| Max Debt to EBITDA | Covenant imposed by the bank syndicate on the LBO loan stating the maximum debt to EBITDA ratio that the target must maintain throughout the duration of the loan. |
| Min Interest Coverage | Covenant imposed by the bank syndicate on the LBO loan stating the minimum interest coverage ratio that the target must maintain throughout the duration of the loan. |
| Deal Size | Total size of the LBO loan (in mil. USD). |
| Term Spread | This variable is used an instrument for LBO loan maturity. Term spread is the difference in yields on ten-year and one-year US government bonds at the time of LBO loan issue as reported by the US Federal Reserve. |
| ***LBO loan syndicate characteristics*** | |
| Syndicate Size | Number of banks participating in the LBO loan syndicate (including lead bank). |
| Members | Number of non-lead member banks participating in the LBO loan syndicate. |
| Lead Bank Share (%) | Total share of the lead bank(s) in the LBO loan. |
| Debt/EBITDA | Total LBO debt divided by pre-deal EBITDA of the target. |
| Syndicate Herfindahl | Sum of squared percentage share of each bank in the LBO loan syndicate. |
| ***Bank network centralities*** *(All centralities are measured over the five years preceding the LBO)* | |
| Diffusion | Expected number of times that information originated by bank *i* is heard by other banks in the network over the time period *T*. Suppose information pertaining to an LBO originates from participating bank *i*, and is broadcast in the first period $t = 1$ among *i*'s neighbors with probability *p*. During each subsequent period, every informed neighbor shares this information and the identity of the source with its neighbors with the same probability *p*. This process is repeated over *T* time periods. The hearing matrix **H** is then defined as: $\mathbf{H}\left(g_y, p, T\right) = \sum_{t=1}^{T}\left(pg_y\right)^t$ where **g** is the $N \times N$ undirected adjacency matrix of the bank network for a given year *y*. The *ij*-th element of **H** is the expected number of times that bank *j* hears some information that originated from bank *i* over *T* previous periods. Banerjee et al. (2013) show that the per-period transmission probability, *p*, can be reasonably well approximated by $1/E[\lambda_1(\mathbf{g})]$,which is the inverse of the largest eigenvalue of the adjacency matrix ***g***. They also suggest that *T* can be approximated by the diameter of the network. *Diffusion* centrality is then defined as: $Diffusion\left(g_y, \mathrm{p}, \mathrm{T}\right) = \mathbf{H}\left(g_y, \mathrm{p}, \mathrm{T}\right) \cdot \mathbf{1} = \sum_{t=1}^{T}\left(pg_y\right)^t \cdot \mathbf{1}$ |
| Sourcing | Expected number of times that bank *j* "hears" information from the other banks over *T* periods. Suppose in each period, a bank receives information originating from various parts of the network. Since $\mathbf{H}(g_y, p, T)_{ij}$ is the expected number of times bank *j* hears information originating from bank *i*, the *j*-th column of **H** denotes bank *j*'s expescted information sourcing from every other bank in the network. *Sourcing* centrality of bank *j* is thus the average of the *j*-th column of **H**. |
| Degree | Number of unique connections of the bank with other banks in the LBO market. |
| Eigenvector | Number of unique connections of the bank with other banks in the LBO market, where each connection is weighted by the eigenvector centrality of the other bank. Represents the bank's ties to prominent and well-connected banks within the network. |
| Network Distance | Length of the shortest path between two banks across the LBO loan syndication network. |
| ***PE characteristics*** | |
| PE Captive (D) | Dummy equal to one if the PE firm is significantly owned and controlled by a financial institution (typically banks or insurance companies), and zero otherwise. |
| PE Age | Age of the PE-sponsor in years. |
| PE Reputation | Total amount of equity funds raised by the PE firms in the five years preceding an LBO deal. |
| ***Bank characteristics*** *(All historical variables are estimated over the five-year period preceding the LBO)* | |
| Bank-PE Relationship | Total volume of LBO loans issued to the PE firm over the last five years in which the incumbent bank participated either as a lead bank or member. This measure is similar to the variable *Bank relationship (amount)* used by Ivashina and Kovner (2011), and applies to the *Lead-PE Relationship* and *Member-PE Relationship* variables used in the empirical analysis. |
| Bank-Target Relationship | Total volume of non-LBO loans issued to the target over the last five years in which the incumbent bank participated either as a lead bank or member. This variable excludes all debt issued as part of the focal LBO transaction, and applies to the *Lead-Target Relationship* and *Member-Target Relationship* variables used in the empirical analysis. |
| Bank-Bank Relationship | Total volume of past LBO loans in the past five years in which two banks *i* and *j* were part of the same loan syndicate. This measure applies to the *Lead-Member Relationship* variable used in the empirical analysis. |
| Non US Bank (D) | Dummy equal to one if the bank is domiciled or headquartered outside the US. |
| Bank Lead Experience (%) | Percentage of participated LBO loans in the last five years in which the bank was the lead arranger. |
| Bank LBO Market Share (%) | Percentage of all LBO loans (in mil. USD) during the previous five years in which the bank participated either as lead or member. |
| Bank-PE Geodist | Great circle geographic distance between the headquarters of the bank and PE firm in kilometers. |
| Bank-Bank Geodist | |

(*continued on next page*)

**Table 1** (*continued*)

| Variable | Definition |
|---|---|
| | Great circle geographic distance between the headquarters of two given banks in kilometers. This measure applies to the *Bank-Lead Geodist* variable used in the empirical analysis. |
| Avg Number of Members | Average number of banks that participated as members in previous LBO loans arranged by the incumbent bank. |
| Average 6 m Spread | Lagged average spread charged by banks on all LBO loans issued during the previous six months, based on Bharath et al. (2011). |
| ***Target characteristics*** | |
| Age | Age of the LBO target in years |
| Assets | Book value of total assets of the target in the year of the LBO. |
| LT Debt to assets (%) | Ratio of long-term debt to total assets of the target in the year of the LBO. |
| EBITDA (%) | Ratio of EBITDA to sales of the target prior in the year the LBO. |
| No Compustat Data (D) | Dummy equal to one if Compustat data is not available for target. |

**Table 2**
Summary statistics for bank characteristics.

| | **Lead Banks** | | | **Syndicate Members** | | | **T-Test** (difference of means) |
|---|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD | |
| Diffusion | 2746 | 8.05 | 7.35 | 5799 | 3.23 | 3.53 | 23.516*** |
| Sourcing | 2746 | 0.08 | 0.05 | 5796 | 0.10 | 0.06 | −6.834*** |
| Degree | 2746 | 1.22 | 0.87 | 5796 | 0.83 | 0.57 | 13.971*** |
| Eigenvector | 2746 | 0.44 | 0.29 | 5794 | 0.28 | 0.18 | 15.072*** |

Table presents summary statistics of network centralities of banks active in the US leveraged buyout (LBO) loan market during the period 1991–2012. A US LBO loan refers to syndicated loans sponsored by US-based PE firms to acquire US-based targets. Syndicate members refers to non-lead (*member*) banks active in this market during this period. A bank is included in the sample if it was active in the US LBO loan market during the five-year trailing period. Data on US LBO syndicated loans comes from LPC Dealscan database and ThomsonOne. See Table 1 for variables description.

**Table 3**
Pairwise correlations between centrality measures.

| | Diffusion | Sourcing | Degree |
|---|---|---|---|
| Sourcing | 0.044*** | | |
| Degree | 0.258*** | 0.330*** | |
| Eigenvector | 0.322*** | 0.484*** | 0.894*** |

Table presents pairwise correlations between network centralities of banks that syndicated in the US leveraged buyout (LBO) loan market during the period 1991–2012. A US LBO loan refers to syndicated loans sponsored by US-based PE firms to acquire US-based targets. See Table 1 for variables description.

median bank has no ties with borrowers. In the case of lead−target and member−target relationships 75% of banks have no ties to LBO targets. These findings highlight that ties are virtually non-existent between banks and PE firms in over half the sample, and even more so among banks and targets.[21]

The median age of the sponsoring PE firm is 17 years and only 8% of them were owned significantly by other financial institutions. Among publicly listed targets for which we have Compustat data, the mean firm size, measured in total assets, is $1.48 billion and median pre-deal EBITDA margin is 13%. This suggests that the LBO targets in our sample (especially those publicly listed prior to their LBO) are large, mature companies which, unlike startups, require significant funding to be acquired.

### *3.2. Evolution of bank networks in the US LBO loan market*

The US LBO loan market has evolved continuously over time. Fig. 2 shows the annual number of banks active in this market

[21] Online Appendix B shows that syndicate characteristics and LBO lending terms are not very different when ties between banks and LBO borrowers are present or absent. While prior literature identifies relationship lending as an important mechanism for mitigating information asymmetries during the lending process (Fang et al., 2013; Ivashina and Kovner, 2011; Sufi, 2007), the absence of such ties in the majority of LBOs implies that other mechanisms are being used for the resolution of information asymmetries. If lead banks have no private information available on borrowers, they may potentially rely on information produced and transmitted by other banks within the syndication network. Table 4 shows that this is indeed a possibility as syndicate members have more or less similar ties as lead banks to PE firms and targets. Member banks could therefore play a key role in facilitating LBO loan provision, particularly when the lead bank does not have sufficient ties with prospective LBO borrowers.

**Table 4**
Summary statistics for LBO characteristics.

| Variable | N | Mean | SD | Min | Median | Max |
|---|---|---|---|---|---|---|
| ***LBO Deal Characteristics*** | | | | | | |
| Deal Value ($m) | 2807 | 303.50 | 395.10 | 24.00 | 207.00 | 5525.00 |
| Loan Spread over LIBOR (%) | 2834 | 3.80 | 1.70 | 0.00 | 3.70 | 11.50 |
| Loan Maturity (months) | 2646 | 66.80 | 14.80 | 12.00 | 68.00 | 120.00 |
| Loan Collateral (D) | 2859 | 0.50 | 0.50 | 0.00 | 0.00 | 1.00 |
| Max Debt to EBITDA | 424 | 5.80 | 1.50 | 1.75 | 5.90 | 11.30 |
| Min Interest Coverage | 346 | 1.90 | 0.50 | 1.00 | 1.80 | 5.00 |
| LBO Debt/EBITDA | 491 | 3.60 | 4.10 | 0.10 | 2.60 | 34.30 |
| Syndicate Size | 2834 | 4.20 | 2.40 | 1.00 | 4.00 | 14.00 |
| No Members | 2832 | 2.30 | 2.30 | 0.00 | 2.00 | 12.00 |
| Lead Bank Share (%) | 2237 | 41.90 | 22.80 | 0.00 | 40.00 | 98.00 |
| Non-US Bank (D) | 2859 | 0.70 | 0.40 | 0.00 | 1.00 | 1.00 |
| ***Bank Characteristics*** | | | | | | |
| Lead-PE Relationship ($m) | 2833 | 108.10 | 350.90 | 0.00 | 0.00 | 5005.00 |
| Lead-Target Relationship ($m) | 2831 | 14.30 | 78.30 | 0.00 | 0.00 | 2288.30 |
| Member-PE Relationship ($m) | 1744 | 79.80 | 252.70 | 0.00 | 0.00 | 1662.20 |
| Member-Target Relationship ($m) | 1744 | 6.70 | 22.60 | 0.00 | 0.00 | 144.20 |
| Lead-Member Relationship ($m) | 1744 | 2048.30 | 2935.90 | 0.00 | 710.00 | 13,498.10 |
| Bank Lead Experience (%) | 2731 | 49.40 | 25.30 | 0.00 | 50.90 | 89.20 |
| Bank LBO Market Share (%) | 2703 | 1.00 | 1.40 | 0.00 | 0.60 | 7.90 |
| ***PE Characteristics*** | | | | | | |
| PE Captive (D) | 2859 | 0.08 | 0.27 | 0.00 | 0.00 | 1.00 |
| PE Age (years) | 2245 | 18.70 | 15.50 | 2.00 | 17.00 | 48.00 |
| ***Target Characteristics*** | | | | | | |
| Target Age (years) | 2379 | 36.50 | 22.80 | 1.00 | 37.00 | 98.00 |
| Assets ($m) | 206 | 1478.80 | 2679.90 | 22.40 | 810.30 | 19,115.60 |
| EBITDA (%) | 206 | 16.00 | 10.00 | −5.00 | 13.00 | 59.00 |
| Debt to Assets (%) | 206 | 42.00 | 28.00 | 0.00 | 42.00 | 118.00 |
| No Compustat Data (D) | 2377 | 0.91 | 0.25 | 0.00 | 1.00 | 1.00 |

Table presents summary statistics for a sample of US leveraged buyout (LBO) loans during the period 1991–2012. A US LBO loan refers to syndicated loans sponsored by US-based PE firms to acquire US-based targets. The primary data sources on LBO deal terms, and bank and PE firm characteristics are the LPC Dealscan database and ThomsonOne. Data on target firm characteristics prior to the LBO is from Compustat. See Table 1 for variables description.

between 1991 and 2012. The number of banks grew almost five-fold during the late-90s, possibly due to the rapid growth in buyout activity following the deregulation of private markets by the National Securities Markets Improvement Act (NSMIA) of 1996.[22] This trend stalled after the Dot-Com bubble burst and then fell considerably after the 2007–09 financial crisis. Much of the activity in the syndicated LBO loan market is due to domestic banks.

Fig. 3 provides six different snapshots of bank networks in the US LBO loan market between 1992 and 2012. Nodes in each graph represent banks that were actively syndicating LBO loans in the previous five years. Blue nodes denote domestic banks and red nodes depict foreign banks. Edges represent connections between two banks based on the intensity of their association in LBO loan syndicates during the preceding five years. Clearly, interactions among bank have intensified substantially in conjunction with the massive growth of the US LBO market in the past three decades. The LBO syndication network has become much more centralized over the years, characterized by a growing number of highly connected banks (visible at the core), both domestic and foreign.

Fig. 4 plots the mean bank centralities per year across the sample period. Mean *Degree* – the mean number of nodes connected to each node – rose until the year 1999 but fell back ever since to its initial levels. The mean of the other centralities – *Diffusion*, *Sourcing*, and *Eigenvector* – have all fallen over time, consistent with a network characterized by growing interconnectedness and an emerging core-periphery structure where some nodes are better connected than others. This is evident in the skewness of the distributions of bank centralities over time, as seen in Fig. 5.

All four centralities have a moderately positive skew, implying the existence of a few highly connected and many sparsely connected banks. The skewness of *Diffusion* peaked in year 2000 but has dropped ever since. This signals that banks in general have become better over time at diffusing information to one another across the syndication network. Skewness of the other three centralities – *Sourcing*, *Degree*, and *Eigenvector* – increased until 2008, but has dropped ever since, which is also consistent with growing interconnectedness.[23]

[22] A recent study by Ewens and Farre-Mensa (2019) shows that NSMIA helped create large PE funds that led to a massive surge in demand for buyouts and growth equity investments.

[23] Online Appendix C provides a visual illustration of the market share of individual banks in the US LBO market by year.

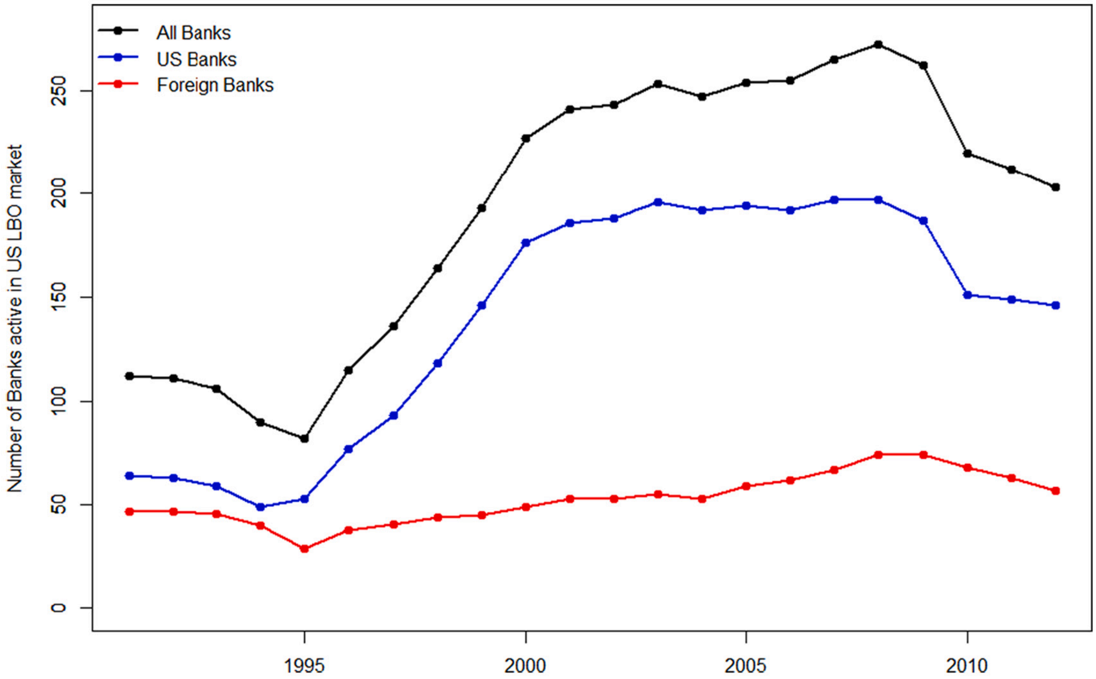


**Fig. 2.** Active banks by year in the US LBO loan market.
Figure shows the number of banks active in the US LBO loan market by year. A bank is considered active in year $t$ if it was involved in at least one LBO in the preceding five years, i.e. between $t-5$ and $t$. Blue line represents banks that are domiciled or headquartered in the US. Red line represents banks domiciled or headquartered outside the US. Black line denotes all banks irrespective of domicile or headquarter location.

### 3.3. Relationship between bank network centralities and reputation

The syndicated LBO loan market is greatly affected by the information asymmetries between lead banks, syndicate members, and borrowers (Ivashina, 2009). These frictions must be alleviated for LBO syndicates to be formed, for deals to be financed, and for the loan market to clear.

In the case of syndicate formation, prior studies note that prospective members rely on reputation of the lead bank in deciding whether to join the syndicate (Carey and Nini, 2007 Ross, 2010 Sufi, 2007). The premise here is that reputation is valuable and serves as a credible signal of the bank's ability to conduct due diligence and screen and monitor borrowers (Dennis and Mullineaux, 2000). In addition, reputation is also beneficial for resolving information asymmetry present within the syndicate (Bharath et al., 2011 Diamond, 1984, 1989, 1991 Ivashina, 2009). Relatedly, papers on loan syndication by Godlewski et al. (2012) and Godlewski and Sanditov (2017) use traditional centralities such as *Degree* and *Eigenvector* as proxies for bank reputation. These studies argue that more central banks attract more attention from other banks in the network, and thus enjoy a reputational advantage that helps them mitigate lending costs.

However, these arguments make the default assumption that more reputed banks (that are topologically more central by design) have better access to information flowing within the network.[24] By their very design, traditional centralities and other proxies of reputation cannot capture information flows (Banerjee et al., 2013, 2019). Being topologically central also does not automatically imply that banks will actively disseminate or seek information from the network. Thus, better constructs that can capture the expected information exchange among banks are required. This is where information centralities become prominent as they encompass an actor's probability to pass information along the network together with the identity of its source (see Sections 2.2.1 and 2.2.2). As such, they do not require implicit assumptions linking reputation to the extent to which banks possess and exchange information.

A natural question then is the extent to which information centralities and traditional centralities differ from each other. While *Diffusion* and *Sourcing* are constructed on the premise that even naïve actors can develop accurate knowledge by simply hearing about each other, it could well be that these centralities merely facilitate the identification of dominant banks in the network. If this is true, then information centralities would be similar to traditional centralities and act as mere proxies for bank reputation. The alternative hypothesis is that information centralities capture how banks interact with each other and share information, and thus represent something different than reputation.

[24] Bajo et al. (2016) make similar assumptions when studying IPO underwriter networks. Hochberg et al. (2007) do the same to examine VC networks.

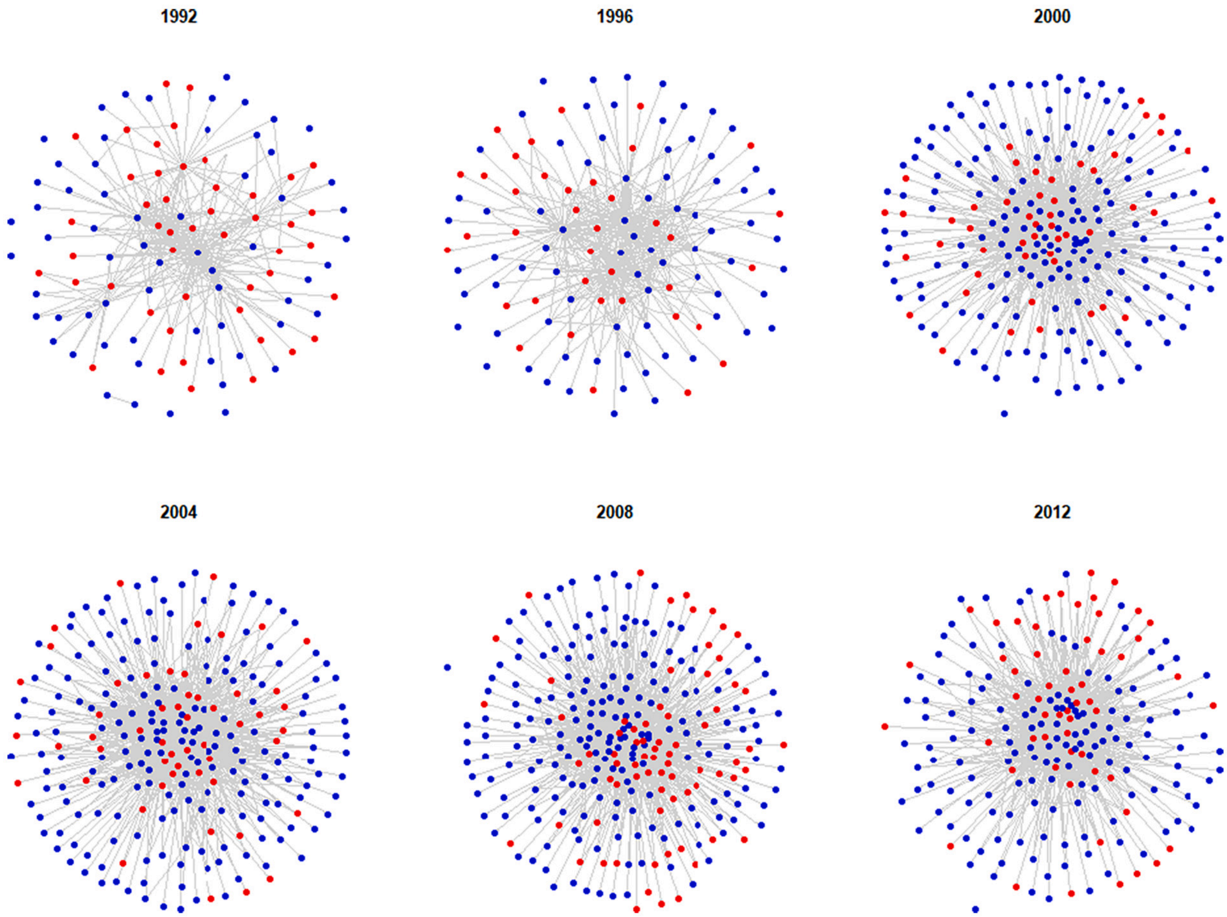


**Fig. 3.** Bank syndication networks in the US LBO market (1990–2012).
Figure presents the ties between banks active in the US LBO loan market during a given year (as shown in the title of each plot). Two banks i and j are considered to have a tie in year t if they were part of at least one LBO loan syndicate in the preceding five years, i.e. between t − 5 and t. The network layout is constructed using the Fruchterman-Reingold algorithm. Blue dots represent banks that are domiciled or headquartered in the US. Red dots represent banks domiciled or headquartered outside the US.

We assess this empirically by modeling the network centrality of a bank as a function of its market share (which serves as an additional proxy for its reputation in the LBO loan market). Formally, we use the following specification:

$$Centrality_{it} = \beta_0 + \beta_1 Bank\ LBO\ Market\ Share_{it} + \alpha_i + \mu_t + \varepsilon_{it} \tag{5}$$

where $Centrality_{it}$ denotes any of our four centrality measures of bank *i* in year *t*, $Bank\ LBO\ Market\ Share_{it}$ is the proportion of LBO loan syndicates (in dollar terms) in which bank *i* participated during the five years preceding year *t* (see Table 1 for definitions), $\alpha_i$ and $\mu_t$ are vectors of bank and year fixed effects, respectively, and $\varepsilon_{it}$ is the error term.

The results presented in Table 5 clearly show that, controlling for bank and time fixed effects, bank market share is not correlated with *Diffusion*. This is consistent with the idea that banks with bigger market shares do not systematically push information into the network, possibly to maintain their dominance and prevent other banks from competing effectively against them. Market share is also not correlated significantly with *Sourcing*, suggesting that reputation, by itself, does not guarantee the bank's ability to acquire information from other banks. In contrast, coefficients of *Degree* and *Eigenvector* are consistently positive and statistically significant, meaning that banks with higher market shares – or reputed banks – occupy topologically central positions within the LBO syndication network. Together with the correlation estimates in Table 3, these findings imply that the information and traditional centralities we employ are quite distinct from one another. We hence expect these measures to behave differently our further analyses of syndicate formation and deal terms.

## 4. Empirical design and results

Our empirical approach is based on the stylized process through which LBO loans are syndicated, as depicted in Fig. 1. We make the simplifying assumption that the lead bank is already chosen to arrange financing for the LBO through syndication. The analysis is

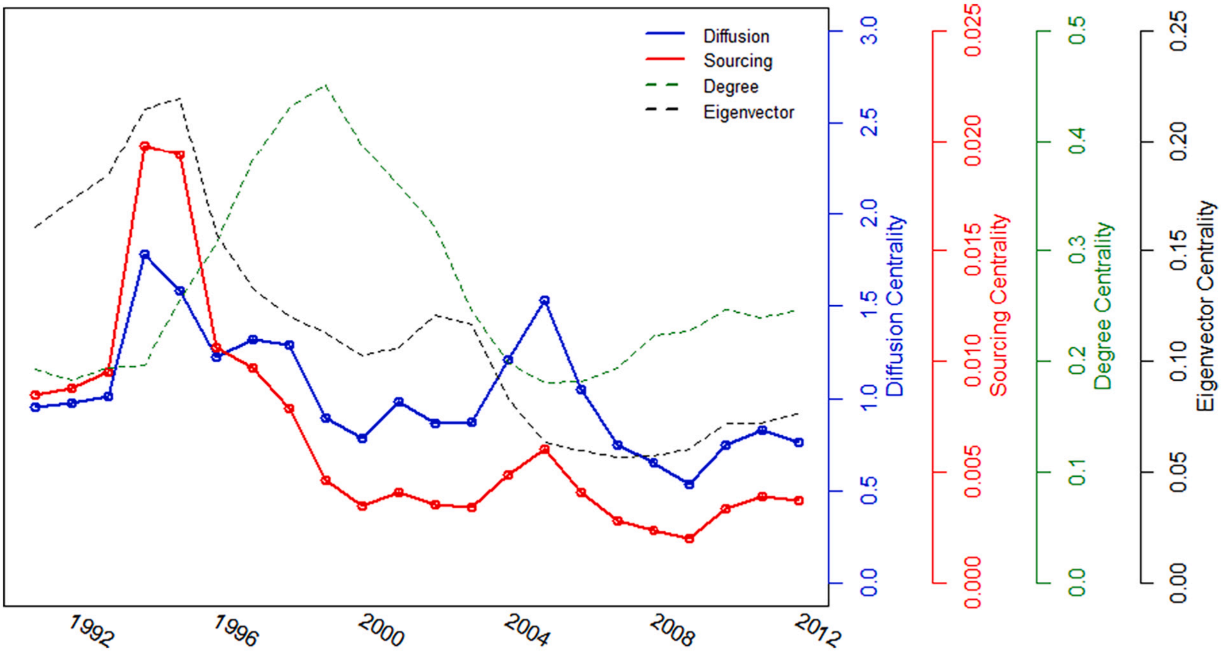


**Fig. 4.** Mean network centralities by year.
Figure presents the distributional properties of bank syndication networks by year in the US LBO loan market. The mean network centralities shown below are computed over a rolling five year window. For each year t, centralityit of bank i is computed based on its syndication activity with other banks in the period t − 5 and t.

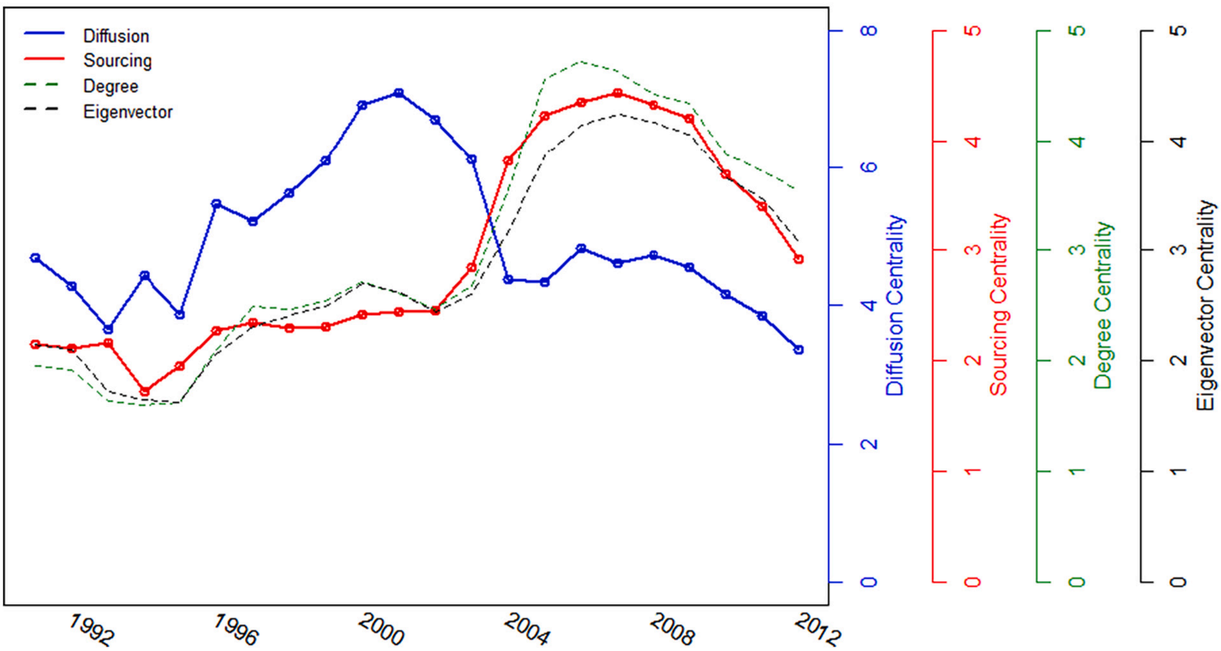


**Fig. 5.** Skewness of network centralities by year.
Figure presents the distributional properties of bank syndication networks by year in the US LBO loan market. The skewness of network centralities shown below are computed over a rolling five year window. For each year t, centralityit of bank i is computed based on its syndication activity with other banks in the period t − 5 and t. Skewness of a variable represents the degree of asymmetry in its probability distribution relative to the normal distribution.

**Table 5**
Relationship between network centralities and bank reputation.

| | (1) Diffusion | (2) Sourcing | (3) Degree | (4) Eigenvector | (5) Diffusion | (6) Sourcing | (7) Degree | (8) Eigenvector |
|---|---|---|---|---|---|---|---|---|
| Bank LBO Mkt Share | −0.098 | 0.232 | 0.211** | 0.272*** | −0.096 | 0.231 | 0.214** | 0.274*** |
| | (0.060) | (0.174) | (0.092) | (0.052) | (0.059) | (0.172) | (0.093) | (0.052) |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | No | No | No | No | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.424 | 0.131 | 0.209 | 0.211 | 0.433 | 0.209 | 0.232 | 0.248 |
| Observations | 22,490 | 22,127 | 22,472 | 22,490 | 22,490 | 22,127 | 22,472 | 22,490 |

Table presents OLS estimates of the relationship between bank network centralities and market share in the US LBO loan market using the following specification:

$Centrality_{it} = \beta_0 + \beta_1 Bank\ LBO\ Market\ Share_{it} + \alpha_i + \mu_t + \varepsilon_{it}$

$Centrality_{it}$ denotes any of our four centrality measures of bank *i* in year *t*, $Bank\ LBO\ Market\ Share_{it}$ is the proportion of LBO loan syndicates (in dollar terms) in which bank *i* participated during the five years preceding year *t*. $\alpha_i$ and $\mu_t$ is a vector of bank and year fixed effects respectively, and $\varepsilon_{it}$ is the error term. The sample spans the period 1991–2012 and is based on adjacency matrices that represent dyadic ties between any two banks in the loan syndication network. Since this network evolves continuously due to the changes in the syndication process, market trends, and the entry/exit of banks, we construct adjacency matrices on an annual rolling basis using five-year trailing windows. These adjacency matrices are then used to compute the relevant network centralities for each bank in the network. Banks that were not active in the market over the five-year trailing period are considered newcomers and have their network centralities set to zero. See Table 1 for variables description.

organized in two stages. First, we investigate whether the network centralities of a candidate bank influence its participation in an LBO loan syndicate and the share retained by lead bank(s) in the syndicate. Second, conditional on successful syndicate formation, we analyze the relationship between lead bank centralities and the LBO lending terms.

### 4.1. Network centralities and syndicate structure

#### 4.1.1. Syndicate participation

We begin by asking whether the probability of a candidate bank's participation in an LBO loan syndicate is influenced by its abilities to share (receive) information with (from) the network.

To perform this analysis, we would ideally need data on banks which joined LBO syndicates as members and those that were invited but did not join. Unfortunately, LPC reports only completed LBO loan syndicates and does not provide data on banks that opted out of joining or were not invited to join. To overcome this limitation and develop requisite counterfactuals for analysis, we could simply consider every bank that participated in an LBO during the five preceding years as a candidate for the given syndicate.[25] For each deal, we could then stack all incumbent members and candidate banks to create a *case-control* sample of LBO syndicate participations.[26] However, this approach implies that the mean lead bank would have to choose among 324 candidates to form an LBO syndicate comprising on average 2 or 3 members. This is unrealistic as attempting to market the loan to so many candidates and sharing information with each of them is implausible from a cost and time perspective.

A more realistic assumption is that lead banks would first approach candidates that are closest to them in activity and characteristics within the syndication network. We therefore construct a case-control sample of LBO syndicate participation using the propensity score (PS) matching method (Dehejia and Wahba, 2002 Rosenbaum and Rubin, 1983).

In particular, we first identify all banks that were active in the LBO market during the five-year trailing period relative to the focal LBO. From these, we identify candidate banks that are closest to the incumbent members along three observable characteristics: prior experience arranging LBO loan syndicates (*Bank Lead Experience*), bank market share (*Bank LBO Market Share*), and domicile (*Non US Bank*) – all determined at the time of the LBO.[27] We then employ PS matching (Dehejia and Wahba, 2002; Rosenbaum and Rubin, 1983) and estimate scalar distance between the vectors of matching characteristics of the incumbent members and each candidate bank. Next, we sort the candidate banks based on this distance and select the ten nearest neighbors. Thus, incumbent members in a deal (*cases*) are matched to ten nearest neighbors (*controls*). All our matching is done with replacement (so that candidates can be used for matching more than once) as it reduces bias in the estimates (Abadie and Imbens, 2002).

Our baseline specification has the following generic form:

$$Pr\left(Match_{ij} = 1\right) = \beta_0 + \beta_1 \cdot Cand\ Centrality_i + \boldsymbol{Controls}_{ij}' \cdot \boldsymbol{\beta}_2 + \mu_j + \alpha_t + \varepsilon_{ij} \quad (6)$$

where $Match_{ij}$ is equal to one if bank *i* is member of the syndicate for LBO deal *j*, and zero otherwise. $Cand\ Centrality_i$ denotes any of our four centrality measures for candidate bank *i*. $Controls_{ij}$ is a set of controls capturing observable characteristics such as prior relationships between bank *i* and the incumbent borrowers that could influence syndicate joining decisions. $\mu_j$ and $\alpha_t$ denote deal and

[25] This is also consistent with the rolling time window we use to construct networks centralities and other variables (see Section 2.1).

[26] A case-control sample of banks created in this manner contains 751,977 observations.

[27] Our PS matching strategy does not account for prior interactions between banks. The reason is that we use these variables as controls in our main empirical analyses. See online Appendix D for a detailed description of our propensity-score matching procedure.

time fixed effects while $\varepsilon_{ij}$ is the error term.

While the PS matching methodology allays potential endogeneity concerns, some unobservable heterogeneity could still bias our results. To resolve this issue and achieve better identification, we use the geographic distance between candidate banks and PE firms (*Bank − PE Geodist*) and between candidate and lead banks (*Bank − Bank Geodist*) as exogenous regressors. The logic stems from prior literature that banks incur distance-related screening and monitoring costs, and prefer to engage with borrowers and other banks in their vicinity (Degryse and Ongena, 2005). The relevance also stems from Sufi (2007) who notes that whenever problems of information asymmetry are more severe, lead banks are likely to choose members that are geographically closer to the borrower. Hence, the key identifying assumption is that geographic distance impacts syndicate formation, while also indirectly affecting LBO lending terms.[28]

Given the dichotomous nature of our dependent variable and deal level matching of the sample, we employ conditional logit (CL) models (McFadden, 1984) to obtain consistent parameter estimates.[29] A major advantage of CL models is that they correctly account for unobservable heterogeneity at the deal level. All such systematic differences are fixed at the deal level, and do not affect the *within-deal* odds of one bank becoming a syndicate member over another. Examples of such fixed deal-level heterogeneity include differences among borrowers and their ties to lead banks.

Our main goal is to understand whether information centralities impact the probability of candidates becoming syndicate members. If banks are better able to, among other things, diffuse and source information from the network, we can expect positive effects of these centralities on the probability to become a syndicate member. However, prior literature states that information can also be gathered through prior lending relationships. It is therefore important to account for these in our models. Following Bharath et al. (2011) and Ivashina and Kovner (2011), we control for prior ties between candidate banks and PE firms (*Bank − PE Relationship*), between candidate banks and targets (*Bank − Target Relationship*), and between candidate and lead banks (*Bank − Bank Relationship*).[30]

Table 6 reports the CL estimates of model (2). Models 1–3 report exponentiated coefficients with robust standard errors. Model 1 suggests that for a candidate bank the odds of joining an LBO syndicate increase by 83.9% (41.5%) for a one-standard-deviation increase in *Sourcing* (*Diffusion*) (both significant at 1% level). The size of the coefficient of *Sourcing* suggests that the ability to source information from the network plays a key role. Similarly, the coefficient of *Diffusion* implies that lead banks might also benefit from any relevant information relayed by candidates. This suggests that controlling for a candidate bank's access to information (via *Sourcing*), prior relationships with borrowers, and geographical proximity to both lead bank and borrowers (all of which are significant), its ability to share information (as captured by *Diffusion*) further enhances its probability of joining the LBO syndicate.

In Models 2 and 3 we test the effects of the traditional centralities *Degree* and *Eigenvector* on syndicate joining (we are unable to include them simultaneously as they are highly correlated). Both centralities have large, positive, and statistically significant effects on the odds of becoming a syndicate member. This is in line with the findings in Table 5, implying that reputation, proxied by the traditional centralities, also plays an important role in syndicate formation.

Lastly, we introduce all the variables in Model 4 and conduct a post-LASSO analysis to pick out the variables most strongly associated with the outcome, $Match_{ij}$. Post-LASSO is a two-step procedure from Belloni and Chernozhukov (2013) in which the first step uses the LASSO method to select the variables that best predict the outcome and the second step applies standard OLS to regress the outcome on these chosen variables.[31] We find that *Diffusion* loses its significance, *Degree* disappears, while both *Sourcing* and *Eigenvector* emerge as strong predictors of syndicate joining (significant at 1% level). A one-standard-deviation increase in *Sourcing* and *Eigenvector* is associated with a 5.3% and 7.1% increase in the probability of joining the syndicate, respectively. This shows that successful syndicate participation depends most on a candidate bank's ability to source information from the network, and also its position within the syndication network. The findings are consistent with the general notion that the syndication network is useful for alleviating potential information problems arising during loan syndication.

A concern with *Diffusion* is that this measure is agnostic of a given syndicate; it captures the ability of a bank to send information to the entire network and not to just any particular lead bank of a focal syndicate. In additional tests, we therefore introduced a more restrictive, deal-specific diffusion measure, which captures the information sharing between the lead and a candidate bank. $Diffusion_{ij}$ thus represents the expected number of times a lead bank $j$ ($j$-th column of the hearing matrix $\mathbf{H}_y$, with $y = 1991, \ldots, 2012$) received information from bank $i$ (i-th row of $\mathbf{H}_y$), evaluated at a time when $i$ is a candidate bank for the focal syndicate of $j$. We run two tests. First, we estimated the correlation between $Diffusion_{ij}$ and the original *Diffusion* measure, which is 0.811 and is significantly different from zero. We then replaced the original *Diffusion* variable with the new $Diffusion_{ij}$ and estimated the model (1) of Table 6. The results were very consistent, and the point estimates are of similar magnitude in both cases. Our findings are hence robust to this alternative specification of *Diffusion*.[32]

[28] In unreported analyses, we include the geographic distance between candidate banks and LBO targets, which were found to be insignificant. This leads to the conclusion that geographic distance between banks and targets may not be a determining factor in the provision of LBO loans.

[29] These are sometimes also referred to as fixed-effect logit models.

[30] In robustness checks, we also measured relationships as the number of interactions in the preceding five years between PE firms and banks, and between targets and banks, respectively. Our findings are robust to these alternatives.

[31] An advantage with a penalized method like LASSO is that coefficients that contribute most to an increase in the squared sum of errors are shrunk to zero. Belloni and Chernozhukov (2013), Belloni et al. (2014a, 2014b) show that running OLS on the variables chosen by LASSO (in the first step) provides consistent estimates.

[32] Given that both these measures yield identical results in regression analyses, we do not present these findings in the paper. These results are, however, available on request. For the same reason, we stick to the original definition of *Diffusion* proposed by Banerjee et al. (2013).

**Table 6**
Bank network centralities and LBO loan syndicate participation.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | CL | CL | CL | Post-LASSO OLS |
| Diffusion | 1.415*** | | | 0.008 |
| | (0.034) | | | (0.005) |
| Sourcing | 1.839*** | | | 0.053*** |
| | (0.081) | | | (0.006) |
| Degree | | 2.184*** | | |
| | | (0.076) | | |
| Eigenvector | | | 2.149*** | 0.071*** |
| | | | (0.070) | (0.006) |
| Ln(Bank–Lead Relationship) | 1.521*** | 1.374*** | 1.359*** | 0.006* |
| | (0.049) | (0.045) | (0.044) | (0.003) |
| Ln(Bank–PE Relationship) | 1.449*** | 1.377*** | 1.372*** | 0.042*** |
| | (0.038) | (0.037) | (0.037) | (0.004) |
| Ln(Bank–Target Relationship) | 1.406*** | 1.387*** | 1.391*** | 0.058*** |
| | (0.034) | (0.035) | (0.035) | (0.003) |
| Non US Bank | 0.987 | 0.873** | 0.858*** | |
| | (0.058) | (0.051) | (0.049) | |
| Ln(Bank–PE Geodist) | 0.971*** | 0.970*** | 0.971*** | −0.004*** |
| | (0.010) | (0.011) | (0.011) | (0.001) |
| Ln(Bank–Lead Geodist) | 0.993 | 0.991 | 0.994 | −0.003* |
| | (0.012) | (0.012) | (0.012) | (0.001) |
| Constant | | | | 0.277*** |
| | | | | (0.036) |
| Time FE | | | | Yes |
| Target Industry FE | | | | Yes |
| Pseudo/Adjusted $R^2$ | 0.178 | 0.178 | 0.179 | 0.107 |
| $\chi^2$ | 1880.787 | 1756.640 | 1849.924 | 37.95 |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 |
| Observations | 21,112 | 21,112 | 21,112 | 21,112 |

Table reports conditional logistic (CL) estimates of the probability of a candidate bank's participation as non-lead member of an LBO loan syndicate according to the following specification:

$Pr(Match_{ij} = 1) = \beta_0 + \beta_1 \cdot Cand\ Centrality_i + \boldsymbol{Controls_{ij}}' \cdot \boldsymbol{\beta_2} + \mu_j + \alpha_t + \varepsilon_{ij}$

The dependent variable $Match_{ij}$ is a dummy term equal to one if bank $i$ was a member of the LBO syndicate for deal $j$, and zero otherwise. $Cand\ Centrality_i$ denotes any of the four centrality measures for a candidate bank $i$ depending on the specification. $Controls_{ij}$ is a set of control variables capturing other observable characteristics such as prior relationships between bank $i$ and the incumbent borrowers that could influence syndicate participation choice. $\mu_j$ and $\alpha_t$ denote deal and time fixed effects while $\varepsilon_{ij}$ is the error term. The sample is constructed using case-control matching, where for each deal, we identify up to 10 candidate banks that are closest to the incumbent members in terms of their propensity scores based on observable characteristics. The matching is done with replacement (so that candidates can be used for matching more than once) as it reduces bias in the estimates. The sample period is from 1991 to 2012 and is at the deal level. See Table 1 for variables description. Coefficients in columns (1)–(4) are reported as odds ratios. Numbers in parentheses are robust standard errors adjusted for heteroscedasticity and clustering at the deal level. ***, **, and * denote that the coefficient is significantly different from zero at 1%, 5%, and 10% level (two-tailed), respectively.

### *4.1.2. Do networks complement or substitute for relationships?*

If bank networks are an important source for enhancing information flows during loan syndication, a natural question arises whether information from the network is as important when banks are aware of the borrowers through prior interactions. This question is important because a prior relationship with the borrower may substantially reduce a bank's dependence on the network for information relevant to the LBO. Under this logic, information centralities and borrower relationships should serve as substitutes. It must be noted, however, that bank−borrower relationships are virtually non-existent in more than half of the deals in our sample (see corresponding median for member−target relationships in Table 4). The scarcity of these ties leads us to believe that the syndication network may serve as an important source of information during syndicate formation.

We investigate these effects by interacting network centralities and borrower ties of candidate banks and report the CL estimates in Table 7. Models 1 and 2 show the interaction effects between information centralities and *Bank-PE Relationship* and *Bank-Target Relationship*, respectively. We repeat this exercise by interacting the traditional centralities with *Bank-PE Relationship* and *Bank-Target Relationship* in models 3 and 4, respectively. Model 5 shows post-LASSO OLS estimates by pooling all the variables of interest and their interaction terms into a single specification.

The coefficients of centralities in Models 1–4 are consistent with the results in Table 6. Coefficients of the interaction terms between *Diffusion* and *Bank-PE Relationship* and *Bank-Target Relationship* in Model 1 are both significant (at 1% level) and slightly below one, implying their negative influence on the odds of joining a syndicate. In Model 2, the interaction between *Sourcing* and *Bank-PE Relationship* is significant (at 1% level) and above one, implying a positive effect on the bank's odds of joining a syndicate. In Models 3 and 4, the interaction terms between a candidate's traditional centralities and borrower ties are significant (at 1% level) and negatively associated with the odds of joining a syndicate. The positive association between *Sourcing* and *Bank-PE Relationship* persists in the post-

LASSO results in Model 5. Similarly, the negative interaction effect of *Eigenvector* and *Bank-Target Relationship* also prevails in the post-LASSO estimation.

Since we use CL models to estimate the odds of a bank becoming a syndicate member, the interaction terms cannot be interpreted directly from the regression output. To better interpret the results, we present the corresponding interaction plots in Fig. 6. Each plot shows, ceteris paribus, the effect of a network centrality over a discretized version of borrower relationship (indicating whether or not prior ties with the borrower exist) on a bank's probability of joining an LBO syndicate.

Plots (a) and (b) show the interaction effects between *Diffusion* and *Bank-PE Relationship* and *Bank-Target Relationship*, respectively, while plots (c) and (d) show the interaction effects between *Sourcing* and *Bank-PE Relationship* and *Bank-Target Relationship*, respectively. The *black* line denotes the situation where candidate banks have no prior ties with incumbent borrowers and the *blue* line denotes the existence of prior ties. Plots (a) and (c) suggest that a candidate bank always has a higher probability to join the syndicate if it has a prior relationship with the PE, irrespective of its *Diffusion* and *Sourcing* centralities. At the same time, the probability of joining the syndicate also increases proportionally with *Diffusion* or *Sourcing* regardless of prior ties. This is consistent with the idea that Bank-PE relationships and information centralities complement each other, i.e., information that is flowing through the bank network is relevant and complementary to information that is gained through prior interactions with the PE.

The situation is slightly different when considering prior ties to the target (plots (b) and (d) respectively). Again, having prior ties to the target increases the probabilities of joining the syndicate. When a bank has no prior ties to the target, both its *Diffusion* and *Sourcing* centralities matter: both significantly increase the probability of joining the syndicate. Specifically, when banks lack ties to the target, their probability of syndicate joining is significantly lower if *Diffusion* or *Sourcing* is low (5th percentile) than when their *Diffusion* or *Sourcing* is median or high (95th percentile). However, when the bank has prior ties to the target, the increase in probability of joining the syndicate increases only slightly for better networked banks, implying that the information gained through the network as reflected by *Diffusion* and *Sourcing* centralities is only slightly complementary to information gained through direct interaction with the target (as the blue lines are relatively flat). Hence, information on the target through previous interactions is highly important, but less than 7% of the candidate banks do have a previous tie with the target company. When no such tie exists, having higher information centralities is important.

The interaction plots for *Degree* and *Eigenvector* are nearly identical (plots (e) − (h)). Even when *Degree* or *Eigenvector* is low, prior ties make it significantly easier to evaluate borrowers and improve a candidate's probability to join the syndicate. The utility of such ties diminishes with greater *Degree* or *Eigenvector* to the extent that their effect is indistinguishable from that of relationships at the right tail of the *Degree* or *Eigenvector* distribution. This suggests that having prior ties to either the PE or the target completely substitutes for having a strong *Degree* or *Eigenvector* network position (95th percentile), and hence that the network position does not bring in complementary information.

Overall, the results suggest that information centralities remain important regardless of whether a bank has prior relationships with borrowers. This implies that lead banks generally benefit from the information sourced and shared by candidates.[33] These findings are also consistent with the idea that the syndication network facilitates access to other types of relevant information than just about the PE and target firm associated with the focal LBO deal.

### 4.1.3. Network centralities and lead bank share

Prior literature states that in the presence of information asymmetries syndicate members require lead banks to hold a greater share of the loan (Bharath et al., 2011 Ivashina, 2009 Sufi, 2007). Understanding the relationship between lead bank share and the cross-sectional variation in leads banks' information centralities is therefore important. The baseline specification we use to investigate this is outlined as follows:

$$\begin{aligned} \textit{Lead Bank Share}_j = \beta_0 + \beta_1 \cdot \textit{Lead Centrality}_j + \beta_2 \cdot \textit{Opaque} + \beta_3 \cdot \textit{Lead Centrality}_j{}^{*}\textit{Opaque} \\ + \boldsymbol{Controls}_j^{'} \cdot \boldsymbol{\beta_4} + \gamma_i + \alpha_t + \varepsilon_j \end{aligned} \quad (7)$$

where the variable of interest is the percentage of the LBO loan retained by the lead bank(s) relative to the syndicate members (*Lead Bank Share*). Since lead bank share is determined after the syndicate is formed, we no longer require the case-control sample or candidate bank centralities used thus far, and instead use deal-level data for the remaining analysis. For each deal *j*, *Lead Centrality* denotes any of our four centrality measures for the lead bank. $Controls_j$ is a set of control variables including prior ties between the lead bank/members and borrowers, ties between lead banks and members, and a variety of controls for deal characteristics. $\gamma_i$ and $\alpha_t$ denote two-digit SIC target industry and time fixed effects while $\varepsilon_j$ is the residual error term.

Our main coefficient of interest $\beta_1$ shows how the lead bank's network centrality influences its share in the LBO loan. We include *Opaque* proxying for the extent to which a lending syndicate must investigate and monitor the target. This variable allows us to differentiate among LBO targets based on their information opacity. The coefficient $\beta_2$ indicates how lead bank share changes with the target's perceived "opacity". The easiest way to measure target opacity is to look at whether the firm was listed on a stock exchange prior to its LBO, and follows from prior studies that regard public firms as being more transparent than private counterparts (Saunders and Steffen, 2011 Saunders et al., 2012). However, this approach is infeasible in our case as only 7% of targets in the sample were

[33] *Diffusion* and *Sourcing* may in fact complement each other. To confirm this hypothesis, we run a regression identical to model (1) in Table 6 with a relevant interaction term. The exponentiated coefficient of this interaction term is 1.647, and is significant at 1% level, which confirms our hypothesis.

**Table 7**
Bank network centralities and LBO loan syndicate participation: impact of relationships.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | CL | CL | CL | CL | Post-LASSO OLS |
| Diffusion | 1.504*** | 1.420*** | | | |
| | (0.040) | (0.033) | | | |
| Sourcing | 1.507*** | 1.493*** | | | 0.024*** |
| | (0.059) | (0.058) | | | (0.006) |
| Degree | | | 2.413*** | | |
| | | | (0.100) | | |
| Eigenvector | | | | 2.242*** | 0.061*** |
| | | | | (0.084) | (0.006) |
| Ln(Bank–Lead Relationship) | 1.585*** | 1.629*** | 1.340*** | 1.328*** | |
| | (0.051) | (0.051) | (0.045) | (0.044) | |
| Ln(Bank–PE Relationship) | 1.528*** | 1.441*** | 1.460*** | 1.452*** | 0.051*** |
| | (0.040) | (0.037) | (0.041) | (0.041) | (0.004) |
| Ln(Bank–Target Relationship) | 1.455*** | 1.409*** | 1.458*** | 1.450*** | 0.074*** |
| | (0.034) | (0.034) | (0.035) | (0.035) | (0.003) |
| Diffusion × Ln(Bank–PE Relationship) | 0.937*** | | | | |
| | (0.011) | | | | |
| Diffusion × Ln(Bank–Target Relationship) | 0.946*** | | | | |
| | (0.011) | | | | |
| Sourcing × Ln(Bank–PE Relationship) | | 1.108*** | | | 0.022*** |
| | | (0.029) | | | (0.004) |
| Sourcing × Ln(Bank–Target Relationship) | | 0.984 | | | 0.004 |
| | | (0.023) | | | (0.004) |
| Degree × Ln(Bank–PE Relationship) | | | 0.866*** | | |
| | | | (0.020) | | |
| Degree × Ln(Bank–Target Relationship) | | | 0.885*** | | |
| | | | (0.018) | | |
| Eigenvector × Ln(Bank–PE Relationship) | | | | 0.889*** | |
| | | | | (0.019) | |
| Eigenvector × Ln(Bank–Target Relationship) | | | | 0.904*** | −0.015*** |
| | | | | (0.017) | (0.003) |
| Constant | | | | | 0.134 |
| | | | | | (0.102) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Pseudo/Adjusted $R^2$ | 0.179 | 0.177 | 0.161 | 0.157 | 0.108 |
| $\chi^2$ | 2171.028 | 1964.079 | 1959.324 | 1910.709 | 32.98 |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Observations | 21,112 | 21,112 | 21,112 | 21,112 | 21,112 |

Table reports conditional logistic (CL) estimates of the probability of a candidate bank's participation as non-lead member of an LBO loan syndicate according to the following specification:

$$Pr(Match_{ij} = 1) = \beta_0 + \beta_1 \cdot Cand\ Centrality_i + \beta_2 \cdot Cand\ Relationship_i +$$
$$\beta_3 \cdot Cand\ Centrality_i * Cand\ Relationship_i + \boldsymbol{Controls_{ij}}' \cdot \boldsymbol{\beta_4} + \mu_j + \alpha_t + \varepsilon_{ij}$$

The dependent variable $Match_{ij}$ is a dummy term equal to one if bank $i$ was a member of the LBO syndicate for deal $j$, and zero otherwise. $Cand\ Centrality_i$ denotes any of the four centrality measures for a candidate bank $i$ depending on the specification. $Cand\ Relationship_i$ denotes prior borrowing relationships between candidate bank $i$ and LBO borrowers (i.e. LBO target or PE firm). $Controls_{ij}$ is a set of control variables capturing other observable characteristics such as prior relationships between bank $i$ and the incumbent borrowers that could influence syndicate participation choice. $\mu_j$ and $\alpha_t$ denote deal and time fixed effects while $\varepsilon_{ij}$ is the error term. The sample is constructed using case-control matching, where for each deal, we identify up to 10 candidate banks that are closest to the incumbent members in terms of their propensity scores based on observable characteristics. The matching is done with replacement (so that candidates can be used for matching more than once) as it reduces bias in the estimates The sample period is from 1991 to 2012 and is at the deal level. See Table 1 for variables description. Coefficients in columns (1)–(4) are reported as odds ratios. Numbers in parentheses are robust standard errors adjusted for heteroscedasticity and clustering at the deal level. ***, **, and * denote that the coefficient is significantly different from zero at 1%, 5%, and 10% level (two-tailed), respectively.

public firms prior to their LBO. To resolve this problem, we use reputation of the sponsoring PE firm as a proxy for target firm opacity. The choice of this proxy stems from two stylized facts. First, the reputation of a PE firm provides information about its LBO target selection and monitoring capabilities, and affects lenders' perceptions on riskiness of the LBO (Demiroglu and James, 2010 Ivashina and Kovner, 2011). Second, PE firms tend to become more conservative and less risk-taking as their reputation grows (Gompers et al., 2016 Ljungqvist et al., 2020). Following these arguments, we define our proxy, *PE Reputation*, as the total amount of funds raised by the PE firm in the five years preceding the LBO.

As the outcome variable *Lead Bank Share* is a fraction, we follow Papke and Wooldridge (1996) and use fractional response regressions to analyze Eq. (3). For LBO loans arranged by more than one lead bank, we take the within-deal averages of lead bank centralities and other characteristics. Finally, the standard errors are robust to heteroskedasticity and clustered at the PE firm level.

The regression estimates are presented in Table 8. The top two rows show that greater diffusion and sourcing capabilities of lead banks result in lower stakes retained by them in the LBO loans. Marginal effects analysis on model (1) shows that a one-standard-

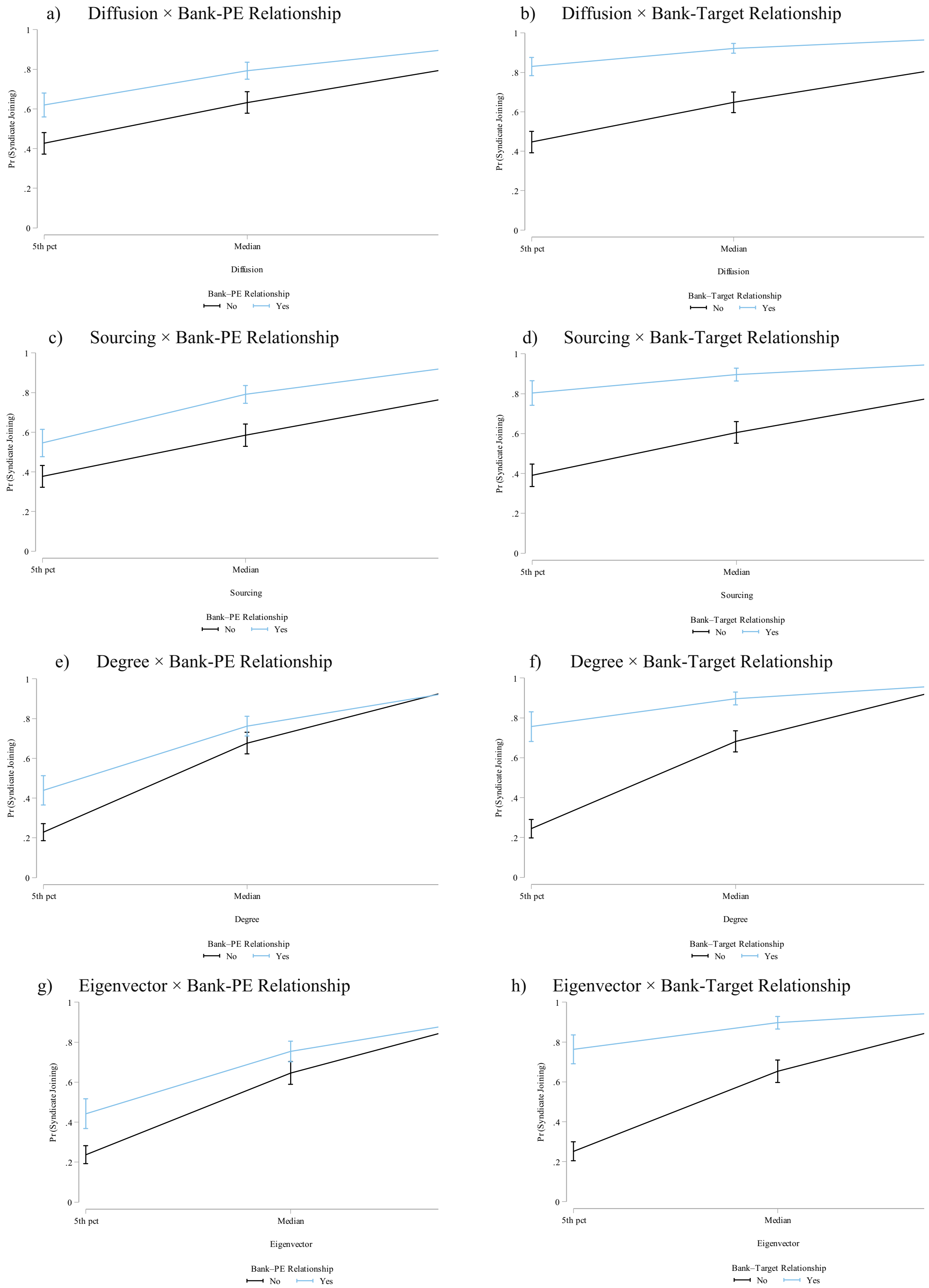


**Fig. 6.** Do bank networks complement or substitute for borrower relationships?
Plots present marginal effects of the interaction terms reported in Table 7. The y-axis in each plot denotes the probability of a candidate bank joining

an LBO loan syndicate as non-lead member. Each plot shows the interaction effect between the network centrality of a candidate bank (Cand Centrality) and a discretized version of prior borrowing relationships between that bank and LBO borrowers (i.e. LBO target or PE firm). Plots (a) and (b) are based on coefficients of interaction terms in model (1). Plots (c) and (d) are based on coefficients of interaction terms in model (21). Plots (e) and (f) are based on coefficients of interaction terms in model (3). Plots (g) and (h) are based on coefficients of interaction terms in model (4). Vertical bars represent the 95% confidence intervals at each level of the running variable (x-axis).

deviation increase in *Diffusion* (*Sourcing*) is associated with a 3.1% (2.6%) reduction in the loan share retained by the lead bank. The interpretation is straightforward. Lead banks that have high information centralities are likely to hear and diffuse more information about the target, about other banks, and about the state of the LBO market, thereby reducing information asymmetries. As a result, syndicate members agree that the lead bank holds a smaller share of the LBO loan.

### 4.2. Network centralities and LBO borrowing terms

After investigating the impact of bank networks on syndicate formation, we now turn our attention to how they affect LBO loan terms. The observable loan characteristics we consider are loan maturity, collateral requirements, and loan interest rates. As outlined in Fig. 1, these terms are set in the final stage of the loan syndication process during deliberations between the lending syndicate and

**Table 8**
Network centralities and lead bank share (%).

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Diffusion | −0.082*** | −0.086*** | −0.082*** | −0.089*** |
| | (0.014) | (0.014) | (0.014) | (0.014) |
| Sourcing | −0.066*** | −0.066*** | −0.082*** | −0.084*** |
| | (0.013) | (0.013) | (0.015) | (0.015) |
| PE Reputation | 0.035* | 0.037* | 0.020 | 0.020 |
| | (0.019) | (0.021) | (0.018) | (0.019) |
| Diffusion × PE Reputation | | −0.040 | | −0.060** |
| | | (0.034) | | (0.029) |
| Sourcing × PE Reputation | | | −0.081*** | −0.095*** |
| | | | (0.026) | (0.029) |
| Ln(Lead–PE Relationship) | 0.082*** | 0.082*** | 0.081*** | 0.080*** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| Ln(Lead–Target Relationship) | 0.058*** | 0.058*** | 0.061*** | 0.061*** |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| Ln(Lead-Member Relationship) | −0.004 | −0.004 | −0.003 | −0.003 |
| | (0.015) | (0.015) | (0.015) | (0.015) |
| Ln(Member–PE Relationship) | −0.117*** | −0.117*** | −0.117*** | −0.116*** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| Ln(Member–Target Relationship) | −0.036** | −0.036** | −0.038** | −0.039** |
| | (0.017) | (0.017) | (0.017) | (0.017) |
| Ln (Deal Val) | 0.033** | 0.034** | 0.033** | 0.033** |
| | (0.015) | (0.015) | (0.015) | (0.015) |
| Lead Non-US | −0.003 | −0.002 | −0.000 | 0.001 |
| | (0.034) | (0.034) | (0.034) | (0.034) |
| Ln (Target Assets) | −0.008 | −0.006 | −0.012 | −0.009 |
| | (0.061) | (0.060) | (0.060) | (0.060) |
| Ln (Target EBITDA) | −0.129 | −0.125 | −0.105 | −0.094 |
| | (0.513) | (0.519) | (0.504) | (0.510) |
| Target LT Debt to Assets | −0.151 | −0.152 | −0.154 | −0.156 |
| | (0.208) | (0.208) | (0.208) | (0.208) |
| No Compustat Data | −0.020 | −0.026 | −0.016 | −0.024 |
| | (0.072) | (0.072) | (0.072) | (0.071) |
| Constant | −0.124 | −0.138 | −0.111 | −0.129 |
| | (0.460) | (0.457) | (0.458) | (0.453) |
| Target Industry FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Observations | 1603 | 1603 | 1603 | 1603 |

Table reports OLS estimates of the relationship between lead bank network centralities and their percentage shareto the LBO loan using the following specification:

$Lead\ Bank\ Share_j = \beta_0 + \beta_1 \cdot Lead\ Centrality_j + \beta_2 \cdot Opaque + \beta_3 \cdot Lead\ Centrality_j * Opaque + \boldsymbol{Controls_j}' \cdot \boldsymbol{\beta_4} + \gamma_i + \alpha_t + \varepsilon_j$

The dependent variable *Lead Share*$_j$ is the percentage of the LBO loan retained by the lead bank in deal *j*. *Lead Centrality* denotes any of our four centrality measures for the lead bank. *Opaque* represents the extent to which the bank syndicate must assess and monitor the borrower, and is proxied by *PE Reputation*, measured as the total amount of funds raised by the PE firm in the five years preceding the LBO. *Controls*$_j$ is a set of control variables for observable deal and borrower characteristics. $\gamma_{ij}$ and $\alpha_t$ denote target industry and time fixed effects while $\varepsilon_{it}$ is the general error term. The sample period is from 1991 to 2012 and is at the deal level. See Table 1 for variables description. Numbers in parentheses are robust standard errors adjusted for heteroscedasticity and clustering at the deal level. ***, **, and * denote that the coefficient is significantly different from zero at 1%, 5%, and 10% level (two-tailed), respectively.

borrowers, with the lead bank serving as an intermediary between them (Bruche et al., 2020 Ivashina, 2009). Our main focus here is to understand the information-related roles played by the lead bank during this final phase of loan syndication, as proxied by its *Diffusion* and *Sourcing* centrality. We hereby focus on the lead bank only, as this bank plays an instrumental role in setting the deal terms.

A potential concern is that LBO contract terms are jointly determined during loan syndication and hence cannot be analyzed independently of each other. This problem has been highlighted by Melnik and Plaut (1986) and Dennis et al. (2000) who model loans as n-dimensional packages in which each dimension represents a specific loan term such as spread, maturity or collateral that cannot be split or traded separately. Banks offer a bundle of these n-dimensional packages to borrowers, allowing them to tradeoff various terms in determining their optimal choice of loan package. This approach suggests that the contractual terms of a loan could be interrelated to each other. While some studies have examined loans (including LBO loans) as multi-dimensional contracts (Bae and Goyal, 2009 Benmelech et al., 2005 Bharath et al., 2011 Dennis et al., 2000 Graham et al., 2008 Qian and Strahan, 2007), none to the best of our knowledge have investigated the effects of bank networks on loan contract terms. Following Dennis et al. (2000) and Bharath et al. (2011), we model loan maturity and collateral jointly and thereafter model loan spread as being determined by the choice of maturity and collateral. We express these choices mathematically using the following system of equations:

$$Maturity = \beta_{10} + \beta_{11}Centrality + \beta_{12}Collateral + \boldsymbol{Controls}_k^{'}\boldsymbol{\beta_{13}} + \boldsymbol{X}_1^{'}\boldsymbol{\beta_{14}} + \varepsilon_1 \tag{8.1}$$

$$Collateral = \beta_{20} + \beta_{21}Centrality + \beta_{22}Maturity + \boldsymbol{Controls}_k^{'}\boldsymbol{\beta_{23}} + \boldsymbol{X}_2^{'}\boldsymbol{\beta_{24}} + \varepsilon_2 \tag{8.2}$$

$$Spread = \beta_{30} + \beta_{31}Centrality + \beta_{32}Maturity + \beta_{33}Collateral + \boldsymbol{Controls}_k^{'}\boldsymbol{\beta_{34}} + \boldsymbol{X}_3^{'}\boldsymbol{\beta_{35}} + \varepsilon_3 \tag{8.3}$$

where *Maturity* is the duration of the LBO loan, measured in log months. *Collateral* is a dummy variable equal to one if the target provided some collateral as security against the loan amount, and zero otherwise. *Spread* is the interest rate charged on the loan (including fees) in excess of the prevailing “London interbank offered rate” (LIBOR).

To resolve the potential endogeneity associated with the co-determination of loan contract terms, we use instrumental variables two-stage least squares (2SLS) regressions to analyze the above system of equations. $X_i$ represents exogenous instruments that identify each equation. Our choice of instruments is based on the prior literature on loan syndication and bank lending.

For Eq. (8.1), we follow Brick and Ravid (1985) and use *Term Spread* as a source of exogenous variation for LBO loan maturity. Term spread is the difference in yields on ten-year and one-year US government bonds at the time of LBO loan issue, as reported by the US Federal Reserve. Brick and Ravid (1985) show that when the yield curve is upward sloping, using longer-term debt is preferred as it increases the present value of tax benefits. Conversely, shorter-term debt is preferred under a decreasing term structure. Since LBOs provide tax shields that allow for the interest paid on debt to be deducted as expense, we expect a positive relationship between LBO loan maturity and term spreads.

For Eq. (8.2), we use *Syndicate Herfindahl* representing the degree of loan concentration within the syndicate as an instrument for collateral. It is measured as the sum of the squared individual shares of each bank (including lead banks) in the LBO syndicate. This instrument choice is due to Sufi (2007), who states that collateral is demanded when the information asymmetry between borrowers and the lending syndicate is high. Concentrated syndicates are able to monitor their borrowers more intensely and hence are expected to demand less collateral.

Lastly, for Eq. (8.3), we use the *Average 6 m Spread* charged by banks on all LBO loans issued in the preceding six months as a source of exogenous variation for loan spreads. Bharath et al. (2011) note that this measure denotes recent trends in the interest rates being charged on syndicated loans and is widely used by banks as a benchmark in pricing new loan issues. DealScan provides this data in the form of pricing grids in which average spreads are specified according to borrower industry, size, and rating. It is therefore plausible to argue that the lagged average 6-month spread has a direct influence on the interest rate spread levied on an LBO loan; however, it is unlikely to have any direct influence on the non-price terms such as loan maturity and collateral.

A final problem in estimating our system of equations is that while spread and maturity are continuous variables, collateral is a binary. We address this issue by using a two-stage estimation in line with Dennis et al. (2000) and Bharath et al. (2011). In the first stage, we use logit models to estimate *Collateral* as a function of all exogenous factors and then use the predicted values from these estimates as additional instruments for collateral in the 2SLS regressions. Bharath et al. (2011) note that this correction provides consistent results of the 2SLS estimation.

The results of the estimations are presented in Table 9. All the regressions control for target industry and time fixed effects. To maintain clarity, we discuss the regression results of each equation separately.

#### *4.2.1. Maturity*

Panel A reports the 2SLS estimates for *Maturity*. The coefficient of *Diffusion* is positive and statistically significant at the 1% level. A one-standard-deviation increase in lead bank *Diffusion* corresponds to 0.11 standard deviations rise in LBO loan maturity. Consequently, syndicate members can determine their monitoring needs more precisely and are hence willing to issue the loan for longer durations. Information flows in the opposite direction, i.e. from the network to the lead bank, might also be relevant, but do not seem to impact loan maturity as shown by the lack of significance for *Sourcing*. None of the other centralities, *Degree* and *Eigenvector*, is significant. This is in line with our previous findings that information centralities take precedence over traditional centralities in the context of LBO financing.

We also estimate the economic significance of the impact of bank network centralities on LBO loan maturity. Based on the coefficients reported in Panel A of Table 9, LBO borrowers obtain loans for a 1.2 months longer duration for a one standard deviation

**Table 9**
Lead bank network centralities and LBO borrowing terms.

**Panel A: Loan Maturity (months)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | IV | IV | IV | IV | Post-LASSO OLS |
| Diffusion | | 0.017*** | | | 0.023*** |
| | | (0.006) | | | (0.006) |
| Sourcing | | 0.005 | | | −0.000 |
| | | (0.004) | | | (0.005) |
| Degree | | | −0.001 | | |
| | | | (0.004) | | |
| Eigenvector | | | | 0.003 | |
| | | | | (0.004) | |
| Ln(Lead-PE Relationship) | 0.003 | 0.001 | 0.003 | 0.002 | |
| | (0.002) | (0.002) | (0.003) | (0.003) | |
| Ln(Lead-Target Relationship) | −0.001 | −0.002 | −0.001 | −0.001 | |
| | (0.004) | (0.004) | (0.005) | (0.005) | |
| Avg Number of Members | 0.016 | 0.016 | 0.016 | 0.016 | 0.027*** |
| | (0.011) | (0.011) | (0.010) | (0.011) | (0.008) |
| Non US Lead | −0.021 | −0.024 | −0.021 | −0.023 | |
| | (0.019) | (0.018) | (0.018) | (0.018) | |
| Ln (Deal Val) | −0.017 | −0.015 | −0.017 | −0.016 | |
| | (0.014) | (0.014) | (0.014) | (0.014) | |
| Captive PE | 0.001 | −0.001 | 0.001 | 0.000 | |
| | (0.022) | (0.022) | (0.022) | (0.022) | |
| Ln (PE Age) | −0.010 | −0.009 | −0.011 | −0.010 | |
| | (0.008) | (0.008) | (0.007) | (0.007) | |
| Lead LBO Mkt Share | −0.000 | −0.000 | −0.000 | −0.000 | |
| | (0.000) | (0.000) | (0.000) | (0.000) | |
| Ln (Target Assets) | −0.031 | −0.036* | −0.031 | −0.031 | |
| | (0.021) | (0.021) | (0.021) | (0.021) | |
| Ln (Target EBITDA) | 0.463** | 0.493*** | 0.463** | 0.465** | |
| | (0.190) | (0.183) | (0.190) | (0.190) | |
| Target LT Debt to Assets | 0.131* | 0.112 | 0.131* | 0.128* | 0.179*** |
| | (0.073) | (0.073) | (0.073) | (0.073) | (0.057) |
| No Compustat Data | 0.016 | 0.020 | 0.017 | 0.016 | |
| | (0.032) | (0.031) | (0.032) | (0.032) | |
| Loan Collateral | 0.098 | 0.072 | 0.098 | 0.096 | −0.063 |
| | (0.120) | (0.126) | (0.119) | (0.118) | (0.072) |
| Term Spread | 0.055*** | 0.051*** | 0.055*** | 0.055*** | 0.055*** |
| | (0.007) | (0.006) | (0.007) | (0.007) | (0.005) |
| Constant | 4.251*** | 4.305*** | 4.251*** | 4.252*** | 4.224*** |
| | (0.175) | (0.181) | (0.176) | (0.174) | (0.079) |
| Target Industry FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.226 | 0.247 | 0.226 | 0.227 | 0.203 |
| Durbin $\chi^2$-test | 0.778 | 0.423 | 0.802 | 0.753 | 1.100 |
| p-value (Durbin $\chi^2$-test) | 0.378 | 0.515 | 0.370 | 0.386 | 0.294 |
| Wu-Hausman F-test | 0.748 | 0.406 | 0.771 | 0.723 | 1.069 |
| p-value (Wu-Hausman F-test) | 0.387 | 0.524 | 0.380 | 0.395 | 0.301 |
| First Stage F-test | 16.583 | 14.746 | 16.955 | 16.988 | 47.467 |
| p-value (First Stage F-test) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Observations | 2178 | 2178 | 2178 | 2178 | 2174 |

**Panel B: Probability of collateral on LBO loans**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | IV Probit | IV Probit | IV Probit | IV Probit | Post-LASSO OLS |
| Diffusion | | −0.114*** | | | −0.172*** |
| | | (0.040) | | | (0.032) |
| Sourcing | | −0.113*** | | | |
| | | (0.040) | | | |
| Degree | | | −0.049* | | |
| | | | (0.027) | | |
| Eigenvector | | | | −0.052* | |
| | | | | (0.029) | |

(continued on next page)

**Table 9** (*continued*)

**Panel B: Probability of collateral on LBO loans**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | IV Probit | IV Probit | IV Probit | IV Probit | Post-LASSO OLS |
| Ln(Lead-PE Relationship) | 0.015 | 0.014 | 0.022 | 0.021 | 0.014 |
| | (0.015) | (0.016) | (0.016) | (0.016) | (0.013) |
| Ln(Lead-Target Relationship) | 0.056** | 0.035 | 0.061*** | 0.061*** | 0.035* |
| | (0.023) | (0.025) | (0.024) | (0.023) | (0.021) |
| Avg Number of Members | 0.142*** | 0.155*** | 0.133*** | 0.138*** | 0.167*** |
| | (0.038) | (0.039) | (0.038) | (0.038) | (0.029) |
| Non US Lead | −0.328*** | −0.283*** | −0.304*** | −0.309*** | −0.280*** |
| | (0.078) | (0.085) | (0.079) | (0.079) | (0.070) |
| Ln (Deal Val) | 0.289*** | 0.295*** | 0.282*** | 0.284*** | 0.317*** |
| | (0.046) | (0.047) | (0.046) | (0.046) | (0.039) |
| Captive PE | 0.193 | 0.153 | 0.203 | 0.206 | |
| | (0.192) | (0.205) | (0.193) | (0.192) | |
| Ln (PE Age) | 0.095* | 0.093 | 0.090 | 0.088 | |
| | (0.057) | (0.060) | (0.057) | (0.057) | |
| Lead LBO Mkt Share | −0.010*** | −0.009*** | −0.011*** | −0.011*** | |
| | (0.003) | (0.003) | (0.003) | (0.003) | |
| Ln (Target Assets) | −0.239* | −0.260* | −0.246* | −0.248* | −0.346*** |
| | (0.129) | (0.133) | (0.130) | (0.129) | (0.102) |
| Ln (Target EBITDA) | −1.346 | −1.077 | −1.396 | −1.365 | |
| | (1.250) | (1.282) | (1.253) | (1.247) | |
| Target LT Debt to Assets | −0.927* | −1.103** | −0.905* | −0.877 | |
| | (0.540) | (0.555) | (0.542) | (0.540) | |
| No Compustat Data | −0.331** | −0.226 | −0.326** | −0.324** | |
| | (0.160) | (0.167) | (0.161) | (0.160) | |
| Syndicate Herfindahl | −0.366** | −0.175 | −0.358** | −0.367** | −0.413*** |
| | (0.166) | (0.179) | (0.167) | (0.166) | (0.138) |
| Ln (Loan Maturity) | 2.083*** | 2.049*** | 2.093*** | 2.044*** | 1.736*** |
| | (0.492) | (0.558) | (0.492) | (0.490) | (0.485) |
| Constant | −6.850*** | −6.835** | −6.769*** | −6.572*** | −6.643*** |
| | (2.537) | (2.830) | (2.539) | (2.533) | (2.524) |
| Target Industry FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| $\chi^2$-test | 364.475 | 363.360 | 368.747 | 369.641 | 447.010 |
| p-value ($\chi^2$-test) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald test of weak instruments | 24.928 | 18.653 | 25.325 | 24.010 | 15.959 |
| p-value Wald test | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Observations | 2174 | 1998 | 2174 | 2174 | 2174 |

**Panel C: LBO loan spread (excess of LIBOR).**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | IV | IV | IV | IV | Post-LASSO OLS |
| Diffusion | | −0.093*** | | | −0.087*** |
| | | (0.033) | | | (0.020) |
| Sourcing | | −0.093*** | | | −0.055** |
| | | (0.032) | | | (0.023) |
| Degree | | | −0.118* | | |
| | | | (0.068) | | |
| Eigenvector | | | | −0.191** | |
| | | | | (0.080) | |
| Ln(Bank-PE Relationship) | −0.001 | −0.052** | −0.066** | −0.088** | |
| | (0.021) | (0.021) | (0.032) | (0.035) | |
| Ln(Bank-Target Relationship) | −0.056** | −0.099*** | −0.115*** | −0.132*** | |
| | (0.026) | (0.024) | (0.033) | (0.034) | |
| Avg Number of Members | −0.194*** | −0.151*** | −0.161*** | −0.131** | −0.178*** |
| | (0.046) | (0.041) | (0.044) | (0.052) | (0.032) |
| Non US Lead | 0.043 | 0.006 | 0.005 | −0.066 | |
| | (0.111) | (0.107) | (0.121) | (0.143) | |
| Ln (Deal Val) | −0.196*** | −0.089 | −0.090 | −0.048 | −0.103** |
| | (0.056) | (0.057) | (0.061) | (0.074) | (0.049) |
| Captive PE | −0.132 | 0.040 | 0.039 | 0.053 | |
| | (0.140) | (0.126) | (0.128) | (0.136) | |

(*continued on next page*)

**Table 9** (*continued*)

**Panel C: LBO loan spread (excess of LIBOR).**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | IV | IV | IV | IV | Post-LASSO OLS |
| Ln (PE Age) | 0.098* | 0.047 | 0.045 | 0.044 | |
| | (0.060) | (0.053) | (0.053) | (0.053) | |
| Lead LBO Mkt Share | 0.000 | 0.000 | 0.000 | 0.000 | |
| | (0.000) | (0.000) | (0.000) | (0.000) | |
| Ln (Target Assets) | −0.332* | −0.261 | −0.293 | −0.417* | −0.042 |
| | (0.183) | (0.198) | (0.194) | (0.241) | (0.136) |
| Ln (Target EBITDA) | −1.189 | −2.261 | −2.101 | −1.269 | |
| | (1.965) | (1.687) | (1.575) | (1.773) | |
| Target LT Debt to Assets | 1.102* | −0.073 | −0.045 | 0.155 | 0.345 |
| | (0.623) | (0.381) | (0.391) | (0.420) | (0.557) |
| No Compustat Data | 0.424** | 0.485** | 0.521*** | 0.584*** | |
| | (0.198) | (0.199) | (0.189) | (0.203) | |
| Ln (Loan Maturity) | 0.191 | −0.036 | −0.108 | −1.762 | −0.798 |
| | (1.722) | (2.188) | (2.097) | (2.847) | (2.036) |
| Loan Collateral | −2.253** | −1.406 | −1.459 | −0.894 | −1.177 |
| | (0.889) | (0.948) | (0.965) | (1.242) | (0.790) |
| Avg 6 m spread | 0.482*** | 0.597*** | 0.651*** | 0.560*** | 0.571*** |
| | (0.102) | (0.101) | (0.095) | (0.129) | (0.094) |
| Constant | 8.565 | 8.634 | 9.336 | 16.779 | 7.167 |
| | (7.426) | (9.437) | (9.323) | (12.528) | (8.960) |
| Target Industry FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.224 | 0.314 | 0.311 | 0.206 | 0.261 |
| Durbin $\chi^2$-test | 8.443 | 5.678 | 4.913 | 5.741 | 0.537 |
| p-value (Durbin $\chi^2$-test) | 0.015 | 0.058 | 0.086 | 0.057 | 0.765 |
| Wu-Hausman F-test | 4.081 | 2.736 | 2.368 | 2.768 | 0.261 |
| p-value (Wu-Hausman F-test) | 0.017 | 0.065 | 0.094 | 0.063 | 0.770 |
| First Stage F-test | 14.396 | 11.863 | 13.705 | 11.950 | 13.572 |
| p-value (First Stage F-test) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Observations | 2115 | 2115 | 2115 | 2115 | 2115 |

Table reports instrumental variables estimates of the following structural model that investigate the effects of the network centrality of lead banks on LBO loan terms:

$Maturity = \beta_{10} + \beta_{11}Centrality + \beta_{12}Collateral + \boldsymbol{Controls_k}'\boldsymbol{\beta_{13}} + \boldsymbol{X_1}'\boldsymbol{\beta_{14}} + \varepsilon_1$

$Collateral = \beta_{20} + \beta_{21}Centrality + \beta_{22}Maturity + \boldsymbol{Controls_k}'\boldsymbol{\beta_{23}} + \boldsymbol{X_2}'\boldsymbol{\beta_{24}} + \varepsilon_2$

$Spread = \beta_{30} + \beta_{31}Centrality + \beta_{32}Maturity + \beta_{33}Collateral + \boldsymbol{Controls_k}'\boldsymbol{\beta_{34}} + \boldsymbol{X_3}'\boldsymbol{\beta_{35}} + \varepsilon_3$

The dependent variable in Panel A is the natural logarithm of LBO loan maturity in months. The dependent variable in Panel B is collateral, which equals 1 if the deal was secured with collateral, and 0 otherwise. The dependent variable in Panel C is LBO loan spread measured in percentage points. Spreads represent the total interest rate (including fees) paid in excess of LIBOR on the loan package. Since LBO deals are typically structured using several loan tranches, all the three dependent variables are value-weighted measures, weighted by the value of each loan tranche relative to the total deal size. We use the instrumental variables approach to analyze the above system of equations and introduce $X_i$ as exogenous instruments to control for potential endogeneity of the corresponding dependent variable. Term spread is the difference in yields on one-year and ten-year US government bonds prevailing at the time of LBO deal origination as reported by the US Federal Reserve. *Syndicate Herfindahl* represents moral hazard within the LBO debt syndicate and is measured using the Herfindahl-Hirschman methodology as the sum of squared percentage shareof each participating bank (including lead banks) to the LBO debt package. The Durbin-Wu tests in Panels A and C determine whether loan maturity and collateral are endogenous in the corresponding models. A rejection of the null hypothesis implies that they must be treated as endogenous variables. The Wald's chi-square test provides a similar test of endogeneity for the IV probit models in Panel B. To test for instrument validity in Panels A and C, we report the first-stage F-statistic that determines the joint significance of the included instruments. A significant F-statistic ($p < 0.00$) implies that our instruments have considerable explanatory power for the endogenous variables. *Average 6 m spread* is the lagged average spread charged by banks on all LBO loans issued during the previous six months, following Bharath et al. (2011). See Table 1 for variables description. Numbers in parentheses are robust standard errors adjusted for heteroscedasticity and clustering at the bank-PE level. ***, **, and * denote that the coefficient is significantly different from zero at 1%, 5%, and 10% level (two-tailed), respectively.

increase in lead bank *Diffusion*. The mean cash savings from this longer duration, when discounted over the holding period (5.6 years) at a mean rate of 5.09% (12-month LIBOR of 1.25% + average LBO loan spread of 3.84%) amounts to \$0.1 million. This translates to a 0.05% increase in return on investment for an initial equity contribution of \$198 million by the PE firm. Further details of these economic effects (and the assumptions made to estimate these effects) are available in the online Appendix E.

Loan maturity also increases with *Term Spread* as predicted by Brick and Ravid (1985). Finally, maturity also increases with target firm profitability (measured as the EBITDA-to-assets ratio).

We conduct several diagnostics tests to verify the validity and relevance of our instrument for *Collateral*. We conduct Durbin-Wu-Hausman $\chi^2$ tests to determine whether *Collateral* is endogenously determined with *Maturity*. The *p*-values of these tests are all above 0.1, suggesting that these terms are set independent of each other. To test for correlation between *Collateral* and its instrument we report the F-statistic from the first stage. The lowest F-statistic value is 14.746, which is above the minimum recommended value of 10 (Staiger and Stock, 1997), thus rejecting the null hypothesis of a weak instrument.

#### 4.2.2. Collateral requirements

Collateral plays an important role in lending as it provides banks with a certain claim against the target's assets in the event of default and reduces the riskiness of debt (Berger and Udell, 1990). It thus helps mitigate problems of adverse selection and moral hazard between borrowers and lenders (Berger et al., 2011 Bharath et al., 2011). However, demand for collateral may be less stringent if the lead bank can leverage its network to resolve these asymmetric information problems.

Panel B shows how lead banks' network attributes affect the probability that a target will be asked to pledge collateral against its LBO loan. The coefficients of both *Diffusion* and *Sourcing* are significant at 1% level and negative in model (2). A one standard deviation increase in *Diffusion* (*Sourcing*) reduces the probability of collateral demand from 50% (average) by up to 16% (13%).[34]

*Degree* and *Eigenvector* are also negative (models (3)–(4)), but the statistical significance is only 10%. Lastly, the post-LASSO estimates in model (5) suggest that only *Diffusion* has a stable negative effect on the probability of imposing collateral. These results suggest that resolution of information problems within the syndicate due to the network diffusion and sourcing capabilities of the lead bank reduces collateral requirements. They also confirm once again that traditional centralities of lead banks are a weaker mechanism to deal with information asymmetry within the syndicate compared to information centralities.

We also find that loans arranged by banks that tend to form larger syndicates are more likely to be granted on a secured basis. This is expected as there is room for shirking of monitoring duties by lead banks of larger syndicates which raises the demand for collateral from members. Expectedly, larger deals have more collateral requirements due to greater credit exposure of the syndicate, whereas loans issued by more reputed banks and to more profitable targets are less likely to have such conditions. Consistent with Sufi (2007), more concentrated syndicates require less collateral because of their more intense monitoring capacity. The coefficients of *Maturity* are positive and highly significant at the 1% level. This is consistent with Boot et al. (1991) who find that longer maturity loans are more likely to be secured given their higher default probabilities.

We address potential endogeneity concerns through tests similar to those reported in Panel A. The Durbin-Wu-Hausman $\chi^2$ test statistics are all highly significant at the 1% level, suggesting that collateral is endogenous to LBO loan maturity. The Wald tests reject the weak instrument hypothesis and thereby confirm *Term Spread* as a valid instrument for LBO loan maturity.

#### 4.2.3. Spreads

Lastly, we test the effect of bank syndication networks on LBO loan pricing. We expect that a lead bank that is able to communicate better through its network should be able to bring down the total cost of borrowing.

We follow Bharath et al. (2011) and posit that LBO loans are priced after the joint determination of loan maturity and collateral. The dependent variable *Spread* is the value-weighted interest rate spread over LIBOR that is charged on the LBO loan package.

Our specifications control for various deal-specific characteristics, prior ties between lead banks and borrowers, lead bank reputation and domicile, as these are known to significantly impact LBO loan terms (Demiroglu and James, 2010 Ivashina and Kovner, 2011). We further control for age of the PE firm and whether it is owned by other financial institutions. Next, we control for target firm quality using three accounting variables *Target Assets*, *Debt to Assets* and *EBITDA margin* based on balance sheet data obtained from Compustat.

Results from the analyses are reported in Panel C of Table 9. In model (2), the coefficients of *Diffusion* and *Sourcing* are both negative and significant at 1% level. In line with the previous results, traditional centralities are only marginally significant up to the 5% level. In fact, both *Degree* and *Eigenvector* drop out in the post-LASSO specification in model (5). This implies that information centralities have stronger effects on LBO loan pricing than their traditional counterparts. The ability of lead banks to diffuse and source information, and thereby reduce information asymmetries, allows the provision of cheaper LBO loans.

Panel C of online Appendix E in provides estimates of the economic significance of these coefficients. LBO borrowers pay a spread that is 13 (11) basis points lower for a one-standard-deviation increase in lead bank *Diffusion* (*Sourcing*). The mean cash savings from these lower interest rates, when discounted over the mean holding period (5.6 years) at a mean rate of 5.09% amounts to $1.2 ($1.02) million, respectively. This is equivalent to 0.6% (0.51%) higher return on investment for an equity contribution of $198 million by the mean PE firm. In comparison, the other lead bank centralities have weaker effects on PE returns.

Consistent with literature, prior lending relationships are also associated with reduced spreads while target opacity (captured by *No Compustat Data*) leads to an increase in spreads. The exogenous instrument for loan spread, *Average 6 m Spread*, behaves as expected with large, positive, and statistically significant effects at 1% across all models.

Diagnostics tests suggest that we cannot unconditionally reject the null of the exogeneity of maturity and collateral. The *p*-values of Durbin and Wu-Hausman tests are at most weakly significant at the 5% level. However, the first stage F-tests reject the null hypothesis of weak instruments across all the specifications.

Lastly, the coefficients of *Collateral* are negative but not statistically significant (through models (2)–(5)). As both non-price terms, *Maturity* and *Collateral*, are endogenous, we re-estimate the models after excluding these terms and obtained similar results. All our specifications include fixed effects for LBO deal year, target industry (two-digit SIC), and lead bank. Reported standard errors are heteroscedasticity robust and clustered at the bank−PE level.

[34] More details are available in Panel B of online Appendix E.

## 5. Conclusions

Syndication among banks is pervasive throughout the LBO market, and to somewhat lesser extent in other corporate loan markets. Previous literature has emphasized the prevalence of relationship lending in these markets, and its central role in resolving information asymmetries between banks and borrowers. However, our analysis of loan-level data on US LBOs shows that lead banks had prior relationships with incumbent borrowers in at most 52% of the deals in our sample. What other channels might banks then utilize to resolve information problems during loan origination despite the scarceness of bank-borrower ties?

In this paper, we show that one such important and accessible channel is the network that develops as banks syndicate repeatedly with each other over time. Our findings show that the spread of information across the syndication network helps banks decide whether to join a syndicate, determine how much to contribute to the loan, and also to negotiate terms with prospective borrowers. We also show that the information flowing through the networks complements the information gained from previous interactions with either the LBO target or the PE sponsor. These results are economically significant: better information access via the network enables banks to issue cheaper LBO loans that provide major cost savings to borrowers.

Overall, our results highlight how network-based information flows might help resolve information problems. This concept was first developed for informal settings to understand how information transmits among members of village communities, or how information diffusion among voters facilitates political targeting. To our best knowledge, ours is the first study to show that these mechanisms play a similarly important role in formal settings such as loan syndication and contracting.

We identify several limitations and propose ideas for future research. Our approach does not allow us to observe actual network information flows. Analyzing the nature and quality of the actual information exchanged over the network, together with the nature and quality of prior interactions with borrowers, may provide better insights on how loan syndication actually occurs. Another interesting question is the extent to which banks are aware of the structure of the network they are embedded into. This is far from trivial given that banks are likely to make careful strategic choices in both how they acquire information and with whom they share it. This will further help relaxing the assumptions about the paths of information transmission and about the probability of this transmission. We leave these as open questions for future research.

## Declaration of Competing Interest

None.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2022.102181.

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