International Review of Financial Analysis 86 (2023) 102527

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Shaking hands with common foes: Clique premium and information diffusion in private equity networks[☆]

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ARTICLE INFO

Keywords:
Private equity
Secondary buyouts
Networks
Information diffusion
ERGMs
Network formation
Financial networks
SBOs
Clique premium
Contagion

ABSTRACT

The fastest growing segment of private equity deals is secondary buyouts (SBOs) sales from one private equity (PE) firm to another. We operationalize a novel *FactSet* database to map the network structures of secondary buyouts between PE firms. We offer three contributions. First, after controlling for economic covariates, we find that PE firms are almost three times more likely to transact if they share a partner, that is both firms belong to the same clique. Second, we find that the profitability of such transactions is unambiguously higher relative to the baseline *only if* these are the result of repeated interaction between firms belonging to the same cliques. In other words, a *clique premium* exists under repeated interaction. Third, we provide evidence that the economic incentive at the core of clique premium may be related to access to information. In fact, we show that information related to transactions diffuses through the network, with 23% and 16% of the information going one and two steps beyond transacting parties, respectively.

1. Introduction

Private markets are at an all-time high, with $5.8 trillion assets under management (McKinsey, 2019). Private equity (PE) firms are the largest economic agent in private markets, representing 31% of total assets under management. Formally, a private equity leveraged buyout (LBO) is when a General Partner (GP) manages an investment that is mainly sponsored by Limited Partners (LPs) to acquire a targeted company.[1] The PE firm creates a closed-end PE fund to raise equity capital, mainly through the contribution of several LPs. The PE firm invests into companies implementing buyouts during the life of the fund (Chen & Wang, 2022). The incentive structure regulating deals is in principle clear: before the buyout process, LPs and GPs agree on the managing fees that will be paid to GPs. The management fees are a percentage of capital committed at the start of the fund. Throughout the buyout process, executives from the targeted portfolio company will sign the Management Services Agreements (MSAs) with GPs and clarify the amount of Transaction and Monitory fees paid. Alternatively, GPs earn the carried interest which is generally 20 percent of the profit realized after the investment. The two contracts involve the three parties in a buyout: GPs, LPs, and executives from the portfolio company, the three types of fees are the representative factor of this trilateral game (Chen & Wang, 2022).

The LBO is a leveraged transaction because only a small portion of the acquiring capital is contributed by the GP and the rest is financial debt (Chen & Wang, 2022). Secondary buyouts (SBOs) are deals in which one PE fund sells a portfolio company to a competitor fund. Amidst the industry driving factors, there has been little research analyzing the *structure* of inter-PE transactions. This paper examines how the PE network, that is the portfolio of companies acquired by PE firms through SBOs, affects the evolution of the market for secondary buyouts.

PE firms are facing challenges to source new investments. PE firms have a record-high amount of uncalled capital at $2 trillion dollars (Bain, 2020). Thus, PE firms are under pressure to deploy capital, and they are searching for new avenues to generate value. Arcot et al. (2015) finds that PE firms under pressure to deploy capital are more

☆ This research is supported by the EU Horizon 2020 Research and Innovation Programme through Marie Skłodowska-Curie Project 101022681, the Australian Research Council through Discovery Project DP170100429 and BPN, Italy grant 2031. The authors are particularly indebted to the Editor B.M. Lucey and two anonymous referees for extremely valuable suggestions. We would also like to thank Mikhail Anufriev, Louis-Ferdinand Céline, David Goldbaum, Corrado Di Guilmi, Hardy Hulley, Justin Lal, Kenny Phua, Talis Putnins, Valentyn Panchenko, Ting Wang, Linda Xiao and participants of seminar at University of Technology Sydney, AMES2019 and CMES2019 for useful comments.

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[1] In the following, we frequently refer to GP and LP as “managing PEs” and “investors”, respectively.

https://doi.org/10.1016/j.irfa.2023.102527
Received 29 July 2022; Received in revised form 27 November 2022; Accepted 10 January 2023
Available online 25 January 2023

likely to engage in secondary buyouts. In fact, PE firms are increasingly deploying their uncalled capital via secondary buyouts, accounting for 38% of all PE transactions in terms of deal value in 2018.

The definition and the measurement of value in LBOs and SBOs are evolving notions, and so it is their assessment (see, for example, Acharya et al., 2013 and Jelic & Wright, 2011). The notion of value has progressively shifted from the operating performance of acquired companies (Jensen, 1989; Kaplan, 1989 and Smith, 1990) to the returns that PEs generate for their end investors. For example, Kaplan and Schoar (2005) studied the deal equity return, measured by internal rates of return (IRRs) net of management fees against the S&P 500 return. Contemporary research has been carried out to bridge between these two strands of literature. For example, Acharya et al. (2013) isolates the effects of operational improvements due to PE ownership *and* the deal's relative market outperformance (after removing the effects of financial leverage) in the context of deals involving Europe-based mature PEs.

Taking as fixed a definition of value, how do PE firms generate value for their portfolio companies and the directionality of value transfers are actively disputed in the literature. Either efficiency or opportunistic motives can explain the raise of SBOs. Following Jensen (1989), if PE firm are endowed with superior governance and incentive mechanisms, it follows that chains of transactions are in the interest of investors. A starting point of this literature is that PE firms have expertise in various domains, and SBOs are the vehicle that enables their skill sets to match and complement (Achleitner & Figge, 2014). For example, if PE firms specialize in different stages of restructuring, then PE firms who specialize in the first stage would sell acquired companies to those PE firms with expertise in the second stage. Alternatively, some managing PE firm may have some unique skills that are put to use to generate additional returns. In this sense, Jelic et al. (2019) provide evidence that governance benefits of the buyout model tend not to be exhausted in the primary buyout stage, but the effects in the secondary buyout phase depend on the nature of PE directors' human capital resource, notably in respect of the balance between board monitoring and advisory roles (see, also Acharya et al., 2013 above).

In contrast to this view, at least part of the growth of SBOs might be generated by special interest operating jointly on the buy and the sell side. Following Arcot et al. (2015), on the buy side, when a PE fund has been unsuccessful to invest in traditional deals, it may resort to SBOs that are quicker to complete, fill the fund's investment record, reduce non-invested capital in anticipation of a new round of fundraising, and accrue additional management fees,[2] even if the transaction is suboptimal to investors. On the sell side, LBOs offer a quick exit for managing PE that cannot sell via trade sale or IPO and that need to liquidate an existing fund or show activity to their investors ahead of fundraising. Hence, SBOs can be the preferred option for managing PEs with adverse incentives who wish to conclude a deal quickly (Arcot et al., 2015).

Even within a strict interpretation of the efficiency framework discussed above, the decentralized nature of the PE market causes frictions that can limit the reach and the effectiveness of SBOs. On one hand, searching for a counter-party with complementary skills can be costly, and as the price for assets is unknown, the price discovery process is critical. On the other hand, the search process can be driven by a multiplicity of reasons. Parallel to this, the decentralized nature of secondary buyout markets is such that critical information (for example, about other firms' transactions) may spread across PE firms in complex ways, thus affecting their operations. The above issues suggest the central hypothesis of our work, that is PE firms may rely on their own relationship network – here proxied by companies acquired by PE firms through secondary buyouts – to improve their allocation efficiency, and the network may have an impact on the way information diffuses across PE firms.

More precisely, in this paper we empirically explore two main hypotheses related to the role of PE networks. First, we ask whether PE firms leverage their networks in order to find counter-parties for further secondary buyout transactions. Given two PE firms, A and B, we explore whether they are more likely to transact if they have a common PE partner C in their relationship network. Such transaction corresponds to a *transitive deal*. Topologically speaking, this coincides with the notion of network *triangle*, and suggest a stronger bond than the one of syndication and clubs.[3] In the language of network theory, if no other PE firm transacted with A, B, or C, it means that these three companies form an isolated *clique*.[4]

If the probability for A and B to transact is positively associated to a common PE partner C (after controlling for non-network incentives), the PE network structure shows to be determinant in motivating inter-firm transactions. Under this hypothesis, we would expect transactions to stem between PE firms characterized already by common investments, and such result should to be robust to firm-specific, sectoral and geographical controls.[5]

Our main finding with respect to the above hypothesis is that PE firms are 2.8 times more likely to transact if they are already part of at least one triangle.

This may consistently motivate why in the PE network secondary buyouts are clustered around a *core* of PE firms. Multiple factors can motivate why firm C can foster transactions between A and B. By looking at the performance of the underlying investment, we are able to isolate the existence of a *clique premium* taking place between PE firms A and B. This is an economic premium which unfolds *conditional on* the triangle between A and B repeating over time (i.e. A and B engage in multiple transactions). Importantly, the result is robust to controlling for traditional determinants such as PE firm type, headquartered region, sector focus, experience, and size. We speculate that to gain the benefits of liquidity provided from secondary buyouts, non-influential (i.e. peripheral) PE firms need to build common connections with influential (i.e. central) PE firms. Our analysis implies that transactions between central PE firms and peripheral PE firms occur less than expected based on fundamental characteristics.[6]

Second, we explore a specific motivating factor of clique premium. By acting as a source of information between A and B, C may reduce levels of information asymmetry for concomitant and future trades. This brings us to our second main contribution, that is an attempt

[2] As mentioned at the beginning of Section 1 the standard fee arrangement in PE market is made by 2% fixed management fee and a 20% performance fee, where the latter is charged on profits made by the fund above a certain predefined benchmark. Since private investments are not traded on an exchange, PE firms report less frequently, and their valuation is based on a model rather than on market transactions. The valuation is, therefore, marked-to-model and creates incentives for managing PE firms to exaggerate fund performance (see, e.g. Jelic et al., 2021).

[3] We postpone the formal definition to Section 4.1.

[4] Formally, a clique is a maximal completely connected subnetwork of a given network (Jackson, 2010).

[5] The presence of a strategic motif behind linkage formation has been observed across multiple domains of social and financial interactions. Pairs of individual entities sharing connections (i.e. "friends") are incentivized to behave more cooperatively (see, for an updated overview, Jackson, 2014). In our settings, we hypothesize and test whether the common "friend" also acts as a *bridge* for information flows between both individuals.

[6] Indeed, PE firms with common fundamental characteristics can leverage each other's expertise to generate value for their portfolio companies (Achleitner & Figge, 2014). Hence, we should expect portfolio companies sharing common characteristics such as the headquarters geographical region or the investment sector are more likely to transact with each other. Dependent on what combination of fundamental characteristics PE firms share, we find they are $1.5-5$ times more likely to transact with each other. For example, PE firms who are in the same region and specialize in the same sector are 3.3 times more likely to transact with each other.

to test whether the network has a role in the *dynamic* transmission of information across PE firms. In decentralized markets, information embedded in past deals may contain a potentially rich set of variables, such as their timing, involved parties (and, notably, PE directors, see for example, Jelic et al., 2019) and specific conditions of underlying contracts. All these elements may contribute in guiding the decisions of market participants relative to future deals (see, for more contextual examples, Li & Schürhoff, 2019; Yarovaya et al., 2022 and Giovannetti, 2021a, 2021b). Therefore, transactions between PE firms can have the role of information signals for neighboring PE firms to identify potential skill synergies from the PE firms involved in the transaction and themselves.[7]

Importantly, we provide first-hand evidence that secondary buyouts *propagate* through the network, leading to *persistent and increased* transactions between interacting PE firms. In particular, we find that on average, information related to transactions diffuses through the network, with 23% and 16% of the information going one and two steps beyond transacting parties, respectively. Other papers have studied information diffusion across other types of financial structures. In particular, Li and Schürhoff (2019) find that information spreads through over-the-counter municipal bond networks between dealers and that execution prices are non-monotone in network size, initially declining with more dealers but increasing once networks exceed 20 dealers. By looking at the merges and acquisition phenomena across industries, Ahern and Harford (2014) investigate how inter-industry relations affect the timing and incidence of merger waves. They find evidence that mergers propagate across the industry network following a wave-like pattern. With an exercise similar to our own, they use graph theory techniques to identify which industries are close and which are distant in the product market network. Accounting for a number of controls, including industry fixed effects and an industry's own lagged merger activity, they find that mergers in close industries have a strong positive effect on an industry's own merger activity after a one-year delay, while merger activity in distant industries has a positive impact after a delay of two or three years.

1.1. Methodology

To empirically test the structure of the PE network, we operationalize a novel *FactSet* database which captures secondary buyout transactions in years 1999–2018. We use the data to map the network structures of secondary buyouts between PE firms, and study the dynamics of inter-firm transactions. To the best of our knowledge, *FactSet* has not been used by prior studies on PE activity.[8] The key novelty of *FactSet* is that it provides granular data between PE firms and the portfolio companies they invest in.

To estimate the likelihood of transactions between two PE firms in the network (i.e., the probability for a new link to be established), we adopt a exponential random graph model approach (see, for other applications, Ahern & Harford, 2014 and Stanfield, 2019). Exponential random graph models (ERGMs) generalize standard conditional logit models by simultaneously estimating conditional logit models of link formation among *all* PE firms in the observed network given a set of controls. Therefore, ERGMs benchmark the likelihood of link formation in the observed network against all possible random networks, yet, similar to multivariate regressions, they also allow for multiple controls to explain the observed relationship structure. Therefore, ERGMs enable us to single out the role of the network at the core of our hypotheses (i.e. PE firms leverage their network to make transaction decisions) by controlling for individual firm features such as the size of PE firms involved in transactions or the likelihood of mutual PE firms transacting with each other. Several papers have investigated the effect of networks on firms' decisions with logit and probit approach. For example, Hochberg et al. (2007) analyzes the effect of venture capital networks on investment performance. However, while in these works networks are captured in terms of reduced-form covariates measuring number of connections across firms or firms' centrality relative to other firms, here we estimate the entire structure of connections. This allows us to relate firms' transaction decisions to more granular geometrical information, and in particular, to test the likelihood of firms to create *transitive* connections.[9]

1.2. Literature review

In this work we contribute to the growing literature on the phenomenology of SBOs. A large body of literature points to the fact that PE firms have accumulated significant economic power over the last decade, as evidenced for example in Stanfield (2019), Gompers et al. (2016), Ewens and Rhodes-Kropf (2015) and Arcot et al. (2015). This is the first paper to document the network of secondary buyouts between PE firms, and it does so by means of a novel *FactSet* database. We also contribute to the literature on networks in decentralized markets. Relationship networks have already been found critical for capital deployment in proximate domains. For example, Li and Schürhoff (2019) finds dealers in the over-the-counter municipal bond market use relationship networks to improve allocation efficiencies and execution speeds. As private markets have grown, both theoretical and empirical papers have explored their dynamics. In particular, theoretical papers have documented network approaches to resolve information asymmetry with long-lived relations (Colliard & Demange, 2017; Glode & Opp, 2014; Babus & Kondor, 2013) contributing to increases in future dealings. Our paper constitutes the first empirical investigation in support of this approach in the context of the PE market for secondary buyouts.

This work belongs to the "bright side" stream of the literature for which LBOs and SBOs contribute in adding economic value to transacted firms which is then passed to investors. Several studies assessing post LBO performance generally show positive changes in output. While we refer the reader to the literature reviews of Cumming et al. (2007) and Kaplan and Stromberg (2009) and Jelic and Wright (2011), it is important to emphasize that such evidence is conclusive only for the first wave of PE-backed buy-out, occurring in the 1980s. Data on more recent post LBO performance is scarce and less promising (Guo et al., 2011). Relative to SBOs, the path to value generation is narrower and primarily due to the complementarities between exchanging PE funds (Degeorge et al., 2016; Jelic et al., 2019). We discuss this more in detail in Section 2.

However, it is important to stress that the definition, the measurement and, crucially, the directionality of value added in PE deals, if any, is disputed in the literature. Opportunistic behavior distorting the measurement and the flow of value can realize throughout the temporal span of PE management (see Jelic et al., 2021 for a comprehensive review). For example, Barber and Yasuda (2017) provide support that PE firms synchronize fundraising with periods in which current performance of their existing funds is peaking, whereas (Jenkinson et al., 2013) find that PE firms tend to inflate net asset value during the fundraising period. Cumming and Walz (2010) report systematic biases in the reporting of fund performance. Importantly, these biases

[7] Synergies can be embedded in the governance mechanism at the core of SBOs: new blood injected into the board on SBO, through new and more PE board representation, may enhance the firm's ability to exploit entrepreneurial opportunities (Jelic et al., 2019).

[8] Previous studies use either *Preqin*, *Standard and Poor's Capital IQ*, *Thomson Financial Security Data Company* (SDC) and *Thomson Financial Venture Economics* databases. For example, this is the case for Arcot et al. (2015), Kaplan and Stromberg (2009), Stanfield (2019) and Hochberg et al. (2007).

[9] To explain this notion, suppose that a PE firm A acquires a business from PE firm B, and B had transacted with PE firm C in the past. A transitive connection realizes if firm A transacts with firm C.

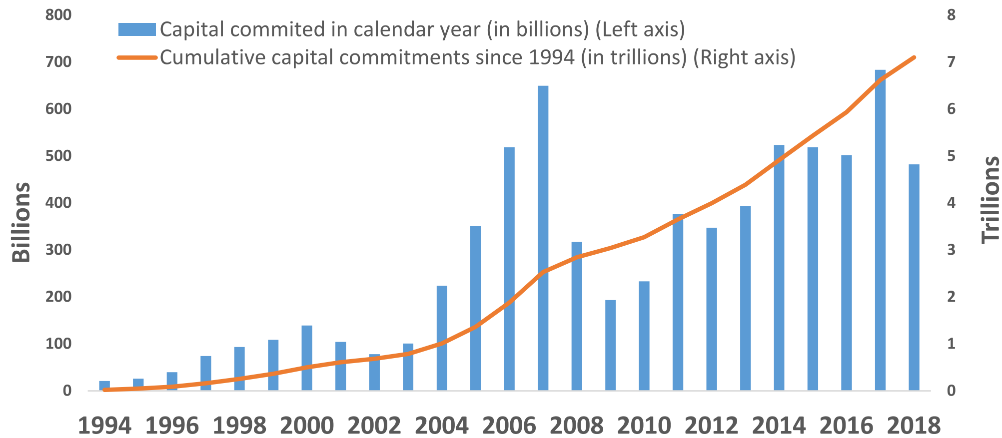

Fig. 1. Capital commitments to the PE industry has grown exponentially since 1994–2018.

correlate with the degree of information asymmetry between investors and PE managing firms. Using a more granular approach based upon portfolio company-level rather than fund-level. Jelic and Wright (2011) uncover further sources of opportunistic behavior that would otherwise be unobservable. In particular, they find that managing PEs under fundraising pressure engage more in upward earnings management. Lastly, other studies such as (Arcot et al., 2015), have shown that SBOs can be an expression of opportunistic behavior rather than a vehicle for value-maximization.[10]

The rest of the paper is organized as follows. In Section 2 we develop our empirical hypotheses on the ground of preliminary analysis and contextualize it with respect to contemporary literature. In Section 3 we present our data. In Section 4 we explain our methodology and construct the benchmark models. In Section 5 we provide results.

2. Hypotheses development

The increasing capital commitments of PE firms (see Fig. 1) can be an indicator of a robust value adding activity of these actors, thus giving support to the efficiency hypothesis mentioned in Section 1. In this perspective, a continuous process of innovation has required PE firms to find new ways to source new investment opportunities (Arcot et al., 2015). SBOs are the fastest growing exit strategy for PE firms. The expanding success of SBOs can be due to the fact that this channel enables PE firms to source new opportunities *directly* from other PE firms.[11]

SBOs directly foster value generation[12] through two main channels (Degeorge et al., 2016). First, a price-driven process. When PE firms engaging in transactions have complementary skills, both PE firms profit from the transaction. The seller obtains a higher valuation compared to other exit opportunities and the buyer has a clear avenue for further valuation creation — in turn leading to a higher subsequent sale price for themselves (see Degeorge et al., 2016). Secondly, SBOs can support the value generating process by enabling liquidity provision by funds under pressure to deploy capital (Arcot et al., 2015).

Indeed, in accordance with the above motives, we may expect to find specific PE attributes as favorable to form transactions between *similar* PE firms. For example, given three PE firms A, B and C, with A and B (respectively, C) characterized by a majority of portfolio companies specialized in bio-pharmaceutical research (respectively, fashion design), it is more likely to observe transactions between A and B rather than A and C or B and C.

Another important dimension which we might expect to drive transactions across PE firms is the type of engineering used by firms. Since the seminal work of Jensen (1989), several studies have researched the capability of PE firms to function as a vehicle for economic growth and innovation. In particular, Kaplan and Stromberg (2009) documents empirical evidence for PE firms to create economic value due to two main channels: *operational engineering* and *financial engineering*. With operational engineering, PE firms leverage their market knowledge to improve the efficiency of the companies they invest in, predominantly through a technical approach (see also Gompers et al., 2016). Financial engineering involves changing the capital structure of portfolio companies to realign the incentive structure for management where management teams have strong equity incentives, to be geared towards "pay for performance" (Bernstein & Sheen, 2016). Management equity ownership helps mitigate the principal–agent conflict by making managers share the economic consequences of their actions with owners. This implies that waste will be reduced and projects more carefully scrutinized for their investment potential, so that firm value and managerial ownership are positively correlated. Here, incentive effects of concentrated ownership, the discipline of debt and effective monitoring by active investors as the key attributes which contribute to value creation in LBOs (Wright et al., 2001).

In network theory, it is common to refer to the tendency of agents sharing similar characteristics to form links with each-other as *homophily*.[13] Hence, we formulate the following

Hypothesis 2.1 (*PE firms are Homophilous*)**.** PE firms endowed with similar characteristics are more likely to transact with each other compared to PE firms with different characteristics.

Hypothesis 2.1 condenses the two motives of direct value creation discussed above, and is important because if verified *against* other

[10] The incentive structure of SBOs is less apparent than other types of deal. Jelic and Wright (2011) finds that post-SBOs performance declines during the first buy-out but in the second buy-out performance stabilizes until year three, after which profitability and efficiency fall while employment increases. Zhou et al. (2014) find strong evidence of a deterioration in long-run abnormal returns following SBO deals. SBOs also perform worse than primary buyouts in terms of profitability, labor productivity, and growth. However, it appears that a PE firm's reputation and change in management are important determinants of improvements in profitability and labor productivity, respectively (see also Acharya et al., 2013).

[11] As described at the end of Section 1.2, an alternative motivation for the expanding popularity of SBOs is opportunistic behavior. The capability of a PE firm to add value to companies that are already under PE ownership has been questioned even by popular media outlets (see, for instance, Economist, 2016).

[12] We refer the reader to Section 1 for the incentive structure of LBOs and SBOs and a discussion on the definition of value in SBO deals and its directionality.

[13] See Jackson (2010) for a primer.

hypotheses of link formation, it would imply that observed PE networks constitute a mechanical by-product of firm-based value creation incentives. As such, networks would have no positive role. However, in this paper we are interested in exploring a complementary channel for value creation. We analyze whether *network-based* incentives have a ground to motivate link formation. Such incentives are *additional* (or alternative) to homophily.

To explore alternative motives for PE firm transactions, we have to look deeper at the structure of the SBO network.[14] We do so by focusing on the entire *distribution* of inter-firm links for a given year of transactions. The idea is that evidence in asymmetries in the distribution of the *number* of per-firm transactions can reflect at macroscopic level that homophily is not enough to motivate the extant structure. *A priori* the analysis, two alternative predictions are equally possible, as it is the case for other decentralized markets (see for example the market for municipal bonds in Li & Schürhoff, 2019). One possibility is that the distribution of linkages across PE firms is random (i.e. Poisson distributed). This would be the case for a competitive market characterized by random search between PE firms with short-lived relationships. In such case homophily can be a sufficient driver for the observed relationship structure. The alternative case is a network made of long-lived trading relationships where a small core of specialized firms attracts the majority of deals with a large group of less connected trading partners (Babus & Kondor, 2013, Li & Schürhoff, 2019, Ozsoylev & Walden, 2011). In the latter case, idiosyncrasies at PE firm level may be driving the link formation process and translate into asymmetries in the observed link distribution. For example, if the age and reputation of a PE firm correlates with performance of underlying investments (see, for example, Acharya et al., 2013), we may expect age and reputation of individual PE firms to affect the link formation process and, more in general, the topology of the network. In such case, we expect the distribution to be closer to a power distribution[15] rather than a Poisson distribution, in line with the literature just mentioned.

In Fig. 2 we address the above by investigating the shape of the distribution of the number of SBO deals per PE firm. Data is extracted from our *FactSet* transactions data-set for a specific year, $t = 2000$. In the upper left (respectively, right) panel, we plot the empirical density of transactions (respectively, transactions made by PE peer firms, labeled as "Partners") per firm. The idea behind comparing these two distributions is to gather first-hand evidence on the existence of macroscopic asymmetries. We observe that most of the firms and firms' PE peers, roughly 83% of the sample, executed less than 10 deals each across the year, with an average of 6.8 deals. However, by comparing the top percentiles of the two distributions, we see that around 1% of firms transacted with more than 20 firms, whereas 1% of firms' partners transacted with more than 15 firms. This indeed suggests an asymmetry in the structure of the partnerships which is indicative of non-randomness of transactions. In the bottom right panel we explore more the asymmetry by opposing the empirical distribution to a Poisson distribution calibrated over the empirical average degree. As it stands clear from the comparison, firms with a small (respectively, large) number of transactions engage in less (respectively, more) trades than expected in a random process.

Lastly, in the bottom right panel we look at the log–log plot the counter-cumulative distribution (CCDF) of transactions.[16] To metricize

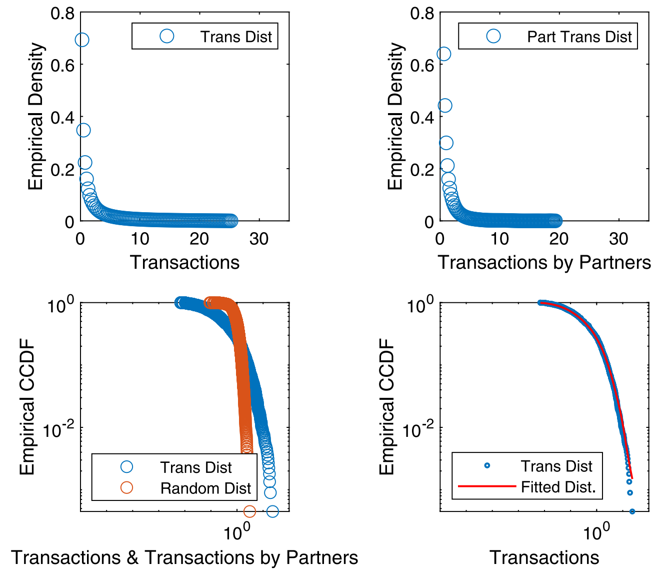

Fig. 2. The distribution of number of SBO deals per PE firm in years $t = 1999$–2017. *(Upper panels)* In the upper left (respectively, right) panel, we plot the empirical density of transactions (respectively, transactions made by PE peer firms, labeled as "Partners") per firm. *(Bottom panels)*. In the bottom left panel we superimpose a Poisson distribution calibrated over the empirical average degree on the empirical distribution of transactions. In the bottom right panel we plot the log–log plot the counter-cumulative distribution function (CCDF) of transactions and fit on it a power law distribution (see main text and Note 2.1 for details).
Source: FactSet.

the asymmetry, we fit a power distribution on the top 20% most active PE firms using the Nadaraya–Watson kernel regression with a bandwidth selected using least squares cross-validation (see Nadaraya, 1964 and Watson, 1964). For comparison purposes, we also run a similar exercise for the distribution of most active partners (untabled). The average slope implied by this non-parametric test is 1.79 for most active PE firms against 2.07 for most active neighbors. We confirm the result estimating the slope with OLS methods. The estimated power distributions[17] closely fit the empirical ones, with a slope coefficient of 1.69 (standard errors equal to 0.11) for the most active PE firms and 1.81 (standard error equal to 0.12) for most active partners, indicating a relatively faster decay for the latter distribution. This indeed provides robust indication that the process underlying the network is non-random, and it signals that the structure may be more balanced than "core–periphery" networks typically observed in other financial environments (see, for a literature review an example in the inter-bank market, Soramäki et al., 2007), where a small number of central "hubs" attracts most of connections from a large number of peripheral firms. We will discuss more in detail this feature in the next section.

Motivated by the above topological asymmetries, we formally ask whether PE firms *use* their relationship networks to source new secondary buyout opportunities from their partners, with what we refer to as *transitive deals*: given two PE firms, A and B, we explore whether they are more likely to transact if they have a common PE partner C in their relationship network. Topologically speaking, this coincides with the notion of network *triangle*, and it hints at a stronger relationship than syndication and clubs.[18] We formalize this idea in the following:

[14] See Section 3 for details of data.

[15] We recall that a power distribution $P(k) \equiv a \cdot k^{\gamma}$ such that $\gamma \in (1,3)$ in which a is a scaling constant and γ is the slope coefficient, has first moment finite and second moment infinite. In that case, the power distribution is an extreme example of the class of *fat-tailed* distributions. This is a class of distributions where there tend to be many more nodes with very small and very large degrees than one would see if the links were formed completely independently (see Jackson, 2010b for examples of the ubiquity of fat-tail structures in social and economic networks).

[16] That is, given $P(k)$ the cumulative distribution of k links, $CCDF(k) \equiv 1 - P(k)$.

[17] For robustness check, in untabulated results we confirmed the estimate using several alternative truncations. To estimate the parameter shape of the power distribution we adopt the methodology of Acemoglu et al. (2012), Section 4. As pointed out by Gabaix et al. (2003), OLS estimates of network distributions are downward biased in small samples. To account for the possible bias, we implement the modified log rank–log size regression they propose.

[18] We postpone the formal construction of triangles to Section 4.1.

Hypothesis 2.2 (*Non-randomness of the PE Network and Existence of Transitive Deals*)**.** After having controlled for homophily, the likelihood of transactions between two PE firms which engaged in at least one common SBO in the past (therefore sharing a network link) is greater than the probability of transacting with other PE firms. In other words, PE firms leverage their existing connections to establish new transactions.

Indeed, from Hypothesis 2.2, it descends that empirical PE network structures have to be statistically different from simulated random networks[19] after controlling for factors of homophily.[20]

However, Hypothesis 2.2 is silent on *why* firms do include the network structure in their own objective function. If short-term transaction-based profit was the ultimate motivation of transitive deals, we would expect a network where the distinctive features discussed above would be diluted into a much more inter-connected and volatile structure. On the other hand, the relative stability of the network suggests that firms are driven by a longer run perspective, where profit develops between interacting firms across multiple transactions. A *clique premium* between any firms A and B engaging in transitive deals through common transacting partners would be particularly evident if – everything equal – the performance[21] of the investment underlying *newly established* transitive deals were not better to the baseline case when compared to subsequent transitive deals involving the same parties A and B. If this is the case, it is clear that only a long-run partnership perspective would sustain the repetition of trades between A and B. This is captured by the following

Hypothesis 2.3 (*Clique Premium of Repeated Transitive Deals*)**.** Given two firms A and B that engage in some transitive deal, the profitability of the underlying transaction is increasing in the number of transactions previously occurred between A and B. In other words, firms engaging in multiple transitive deals enjoy a clique premium.

The literature analyzing the effect of repeated interactions between PE and other actors is active and far-reaching. Ivashina and Kovner (2011) show that PE-backed companies can borrow at a lower cost from banks with which the PE firms have *repeated* interactions, thus improving the odds of a successful exit. Important for our work, a large literature on PE clubs highlights both bright and dark sides of repeated interaction and reciprocity between PE investors. Axelson et al. (2013) bring evidence that highly reputable PE firms are less susceptible to risk shifting as they have incentives to maintain their reputation. Research on collusive practices by PE firms has produced positive evidence on consortium bidding in LBOs, aimed at reducing competitive auctioning (Officer et al., 2010). By comparing the performance of companies undergoing multiple SBOs, Bonini (2015) find that value creation in follow-up deals is limited. Other important studies providing evidence on SBO performance using portfolio company level data are Jelic and Wright (2011) and Zhou et al. (2014). However, follow-up SBOs can be a rational portfolio diversification strategy for risk-averse PE firms. Furthermore, the role of SBOs in diversification is facilitated by some form of "reciprocity": PE managers buy from each other in SBOs to maximize their invested capital and sustain returns, thus arguably increasing the likelihood of further future fundraising.

In this paper we proxy performance with a binary indicator such that an investment is profitable if the underlying company is exited via any channel other than bankruptcy, and exit takes place within 11 years from acquisition,[22] and use it to explore the existence of a clique premium. We posit that the clique premium has two interconnected roles. First, it positively affects the performance of the underlying investment. Second, it constrains the diffusion of information across PE firms. More precisely, we ask the following question: can information from deals *sequentially* travel across the PE network, compared to spreading uniformly? In other words, suppose PE firm A acquires a business from firm B, and B had transacted with firm C. Can information about transactions of A travel to C and influence C's operations and cascade further away? Empirical literature studies the role of networks in the transmission of information in financial markets. Financial markets are driven by investors and traders who, in turn, communicate with each other via their social networks. Shiller and Pound (1989) name the phenomenon "contagion of interest". This may lead to similarities of opinions.[23] We proxy the effects of propagation to information diffusion, as each SBO deal has information contents specific to the PE firms involved in the transaction. Hence, if SBOs propagate in the network, the initial transactions could be diffusing information[24] into the broader network. Li and Schürhoff (2019) finds information diffuses in the over-the-counter municipal bond network between dealers. They confirm that actors in a decentralized market are incentivized to diffuse information and this increases the efficiency of asset allocation. Given the decentralized nature of the PE market, Information diffusion may be critical for efficient asset allocation in this context as well. For example Stanfield (2019) find that low skill PE firms syndicate to pool skill, resources and information to overcome firm-specific deficiencies. Grounded on the above evidence, we produce our concluding hypothesis

Hypothesis 2.4 (*Information Diffusion Across the PE Network*)**.** In the PE network, information about a transaction diffuses beyond direct connections with decay. PE firms more than one link away from a transacting firm have an increased likelihood to engage in SBOs in the next period, yet the increase in the likelihood falls in the network distance from the transacting firm.

3. Data

To our knowledge, this study is the first exploration of PE activity through the *FactSet* database.[25] Compared to other studies (see Footnote) our database is very extensive. It contains a global sample of $n = 7,613$ secondary buyouts backed by $N = 2,230$ PE firms. The

[19] Notice that link formation devised in Hypothesis 2.2 is motivated by individual-based incentives which abstract from game-theoretic considerations, and as such it does not condition a firm's linking decision to other firms' linking decisions.

[20] Formally, Hypothesis 2.2 is referred to as *structural transitivity* (correlation in links due to utility incentives) as opposed to *homophily* (correlation in links due to individual characteristics). See, for a discussion, Graham (2015).

[21] Indeed, we emphasize that this work belongs to the "bright side" stream of the literature for which SBOs contribute in adding economic value to transacted companies within the efficiency hypothesis discussed in Section 1. Opportunistic behaviors such the one discussed in Section 1.2 can justify the existence of cliques, but a connection with clique premium would be less obvious.

[22] As stated in the introduction, the overwhelming majority of funds use 2% for management fees and 20% as their carry level. The amount of carried interest depends on the timing and exit values of portfolio companies, hence the link between performance and timing of exit is potentially complex. In Section 4.3 we describe our methodology in detail, provide supporting references and propose robustness checks against an alternative company-level performance indicator.

[23] Similarities of opinions may also be a result of exposure to common cultural biases or geographic and social proximity, see Kelly and O. Grada (2000), Guiso et al. (2006) and Ivković and Weisbenner (2007).

[24] As mentioned in Section 1, in decentralized markets information embedded in past deals may involve a potentially rich set of variables, such as their timing, involved parties (and, notably, PE directors, see for example, Jelic et al., 2019) and specific conditions of underlying contracts.

[25] Databases used in the literature are *Preqin*, *Standard and Poor's Capital IQ*, *Thomson Financial Security Data Company* (SDC) and *Thomson Financial Venture Economics*, as evidenced in the works of Stanfield (2019), Arcot et al. (2015), Kaplan and Stromberg (2009) and Hochberg et al. (2007).

Table 1
Descriptive statistics of PE firms in the *FactSet* database used in the analysis. The sample consists of 2,230 PE firms that backed transactions between 1999–2017. *Region* section provides the headquarters location breakdown of each of the PE firms. *Secondary Buyouts (Unique)* indicates all the SBOs between PE firms from 1999 to 2017. Given the mutually exclusive definition of financial (resp., operational) engineering in the main text, transactions can take place between PE firms either within the same category (i.e. *Fin.Eng. - Fin.Eng.* and *Ope.Eng - Ope.Eng.*) or across categories (i.e. *Fin.Eng. - Ope.Eng.*).

	N	Mean	Std. Dev.	Min	Median	Max
PE Firm Characteristics						
Assets Under Management ($Mil)	2230	2532	9558	0	280	154,591
Amount of funds		4.4	5.9	1	3	89
Years of experience		22.4	20	0	18	146
Region						
Africa	32					
Asia	82					
Europe	842					
Latin America	13					
Middle East	29					
North America	1191					
Pacific	41					
Total	2330					
Secondary Buyouts (Unique)						
Fin.Eng. - Fin.Eng.	5517					
Fin.Eng. - Ope.Eng	1933					
Ope.Eng - Ope.Eng	163					
Holding Period (Years)		5.5	3.1	0.01	5	36
Transaction Value ($Mil)		712.4	1080.70	0.08	330	10,000

structure of the data smooths concerns related to selection bias: out of k = 78,842 transactions, the proportion of secondary deals is about 10.64%. Roughly 4.95% of all transactions are exited via IPO, while 11,025 deals (corresponding to 13.98% of the total) involve businesses incurring in bankruptcy or resulting in holding period above 11 years.

We report the descriptive statistics of the data-set in Table 1. In the data-set, the majority of PE firms are headquartered in North America and Europe. On average, PE firms are managing 2,532 million assets ($USD). In the table, PE firms with zero assets under management are those which have not disclosed their AUM to the public.[26] Each PE firm raises 4.4 funds on average. This is reflective of the multiple types of PE firms tend to raise in succession to deploy capital to new opportunities. *Years of experience* is reflective of when the PE firm was established and the date until December 2017. The average years of operation in the sample is 22.4 years. *SBOs (Unique)* is reflective of all the secondary buyouts between PE firms from 1999 to 2017. Given the mutually exclusive definition of *financial* (respectively, *operational*) *engineer* provided in the previous paragraph, transactions take place between PE firms either within the same category (i.e. *Fin.Eng. - Fin.Eng.* and *Ope.Eng - Ope.Eng.*) or across categories (i.e. *Fin.Eng. - Ope.Eng.*).

We notice that SBOs predominantly involve PE firms belonging to the former category. A growing literature highlights the importance of financial engineering for positive post-SBO performance (see Jelic et al., 2019 and the literature cited in there). At the core of financial engineering – and also critical for our work – there is the idea that the PE directors involved in financial engineering will try to optimize the boards of their portfolio companies leveraging on their own *human capital* (Jelic et al., 2019), in particular by using their knowledge of the sector (Acharya et al., 2013) and by exploiting their own *social networks* to hire and monitor the best candidates for executive teams (Jelic & Wright, 2011). Our work contributes to shed some light on one of the determinants of the human capital dimensions involved in financial operations, the social network.[27]

Transactions are on average worth $712 million, with a maximum of $10 billion worth a transaction. The average holding period for a company backed by a PE firm that has a company being transacted via secondary buyout is 5.5 years, with the longest recorded holding period of 36 years.

Table 2
Fund types in FactSet and amounts of funds raised.

Type of fund	Amount of funds
Buyout	13,102
Later stage	6453
MBO	3170
Real estate	2367
Debt	2063
Early stage	1936
Fund of funds	1920
LBO	1909
Mezzanine	1182
Infrastructure	693
Seed stage	689
Secondary	468
Total	35,952

Importantly, each recorded transaction includes the identifiers for both buyer and seller PE firms and the transacted company, along with timestamps and the entry and exit strategies. We use the latter information (see also Table 2) to classify PE firms in two mutually exclusive categories, *financial engineer* and *operational engineer*. These depend on the strategy PE firms use to promote their funds.[28] Financial engineer (respectively, operational engineer) is a PE firm raising funds focused on strategies based on *leveraged buyouts* (respectively, focused on *early stage* or *seed stage* funds).

In Table 3 we report the mixing matrices of all PE firms transactions occurring in our data-set according to three qualifiers, respectively given by *Region*, *Sector* and *Firm Type*. We described the first and the third qualifiers in the previous paragraph. *Sector* is obtained by matching the company name with the respective Primary SIC Division Identifiers. We notice that most of recorded transactions occur between firms in North America and Europe and in Manufacturing and Services divisions and are executed between Financial Engineering PE Firms. We also notice that the majority of transactions are made by Financial Engineering firms, with only 2.14% of all transactions taking place between Operational Engineer firms.

Our analysis is at deal level. We operationalize the data-set in two complementary ways. First, we will employ a pooled version

[26] When conducting the network analysis, these will be treated as missing observations.

[27] We thank an anonymous reviewer for this observation.

[28] We refer the reader to the introduction of Bernstein and Sheen (2016) and reference therein for a further characterization of these two classes of operations.

Table 3
The below tables describes the mixing matrices of all PE firm transactions in years 1999–2017 (source: *FactSet*) generated through the *Region* (top table), *Sector* (middle table) and PE firm type (bottom table) qualifier as described in the main text.

Geographic area	Africa	Asia	Europe	Latin America	Middle East	North America	Pacific
Africa	11						
Asia	4	16					
Europe	22	67	1563				
Latin America	1	1	5	1			
Middle East	0	1	28	1	3		
North America	32	113	2278	6	35	3284	
Pacific	1	7	51	0	2	68	12

Sector	Construction	Finance	Manufacturing	Mining	Retail trade	Services	Transp.	Wholesale
Construction	4							
Finance	20	58						
Manufacturing	62	324	786					
Mining	5	12	52	1				
Retail trade	4	16	94	5	8			
Services	129	642	2226	87	146	2151		
Transp.	12	39	96	10	8	202	24	
Wholesale	4	36	147	5	8	172	9	9

PE firm type	Financial engineer	Operational engineer
Financial engineer	5517	
Operational engineer	1933	163

of the transaction set covering the entire 1999–2017 span to generate the complete transaction architecture (analyzed in Section 4.2). This will allow the study on the determinants of transactions of Section 4.4. To study information diffusion in Section 4.4.3, we generate a dynamic transaction architecture in which information spreads via pre-established inter-firm connections (Shiller & Pound, 1989). Inter-firm connections are captured by realized trades. As detailed in Section 4.4.3, to construct the dynamic structure we use a 5-years trailing window[29] in the spirit of Hochberg et al. (2007).

4. Empirical analysis

4.1. Measuring distance between PE firms

At the core of this paper lies the idea that PE firms condition their future transaction decisions on the structure of realized transactions. Network analysis allows us to convey topological regularities into our empirical investigation (see, for a similar approach Hochberg et al., 2007). Formally, given N the set of PE firms in our data-set, and two PE firms i and j such that $i, j \in N$, a *link* $(i, j)_t$ between i and j exists in period t if a transaction between the two firms is recorded in *FactSet* in period t. The PE *network* is represented with a $n \times n$ symmetric matrix $\boldsymbol{A}_t$ where $a_{ij,t} = a_{ji,t} \in \{0, 1\}$. A link between i and j exists (respectively, does not exist) if $a_{ij,t} = a_{ji,t}$ and $a_{ij,t} = 1$ (respectively, $a_{ij,t} = a_{ji,t} = 0$). The assumption of symmetry governing matrix $\boldsymbol{A}_t$ implies that the network representation of the transaction structure is *undirected*, or, in other words, links are bilateral. This is a natural assumption in our context. Albeit transactions are indeed directional, double coincidence of interests is required for a transaction to realize (i.e. for the link to be established). Moreover, firms cannot prevent counter-parties from observing their own transactions, hence information across links can move in both directions.

We define *distance* between two firms $i, j \in N$ at period t as the *smallest* number of transactions (i.e. firms) separating the two firms from each other. To do so, we construct the $n \times n$ symmetric matrix $\boldsymbol{D}_t^k$ with generic element $d_{ij,t}^k \in \{0, 1\}$, $k = 1, 2, \ldots, n$. Element $d_{ij,t}^k$ takes value 1 (respectively, 0) if the minimum number of transaction separating firm i and j in network $\boldsymbol{A}_t$ is exactly k. Indeed, it holds that $\boldsymbol{D}_t^1 = \boldsymbol{A}_t$. Lastly, we provide the formal representation of *clique*. This coincides with the geometrical notion of network *triangle*. Formally, given three firms $i, j, k \in N$, a triangle $T_{ijk,t}$ is defined as $T_{ijk,t} \equiv a_{ij,t} \times a_{jk,t} \times a_{ik,t}$, whereby $T_{ijk,t} = 1$ (respectively, $T_{ijk,t} = 0$) means that the triangle exists (respectively, does not exist). In our analysis, triangles (i.e. cliques) are operationalized to capture *transitivity* of transactions between firms, that is the likelihood that given three firms $i, j, k \in N$ such that $a_{ij,t} = a_{jk,t} = 1$, also $a_{ik,t}$ exists. We exemplify the above notions in the following empirical example

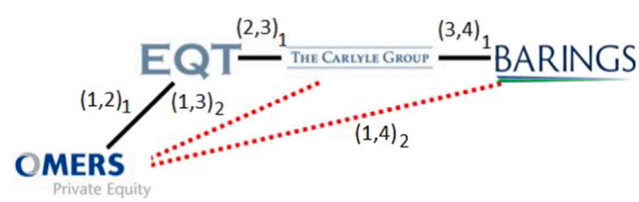

Fig. 3. Representation of the transaction network emerging from Example 4.1. Black bold (respectively, red dotted) lines indicate transaction taking place in 2012 (respectively, 2013).
Source: FactSet.

Example 4.1 (*Clique formation*)**.** Consider four PE firms, *OMERS*, *EQT*, *The Carlyle Group* and *BARINGS*,[30] labeled with numbers 1 – 4 for convenience, and the following five transactions taking place between these firms as extracted from *FactSet*

1. In August 2012, *OMERS* bought *Midland Cogeneration Venture* (a power-plant in Michigan) for $1.66 billions from *EQT*.
2. *EQT* acquired *Automatic Software GmbH* (a technology company) from The Carlyle Group for $270mil in August 2012.

[29] In untabulated analysis we checked for trailing windows of 3 and 7 years respectively which confirm the lack of sensitivity issues, albeit analysis run with the 7 year trailing window has reduced significance.

[30] *OMERS* is one of Canada's largest pension funds and manages $97 billions in net assets. Its PE division operates the group's alternative assets arm. *EQT* is a PE firm focused on infrastructure. *The Carlyle Group* and *BARINGS* are large global PE firms specialized in aerospace, real estate, technology, telecommunications and media among other sectors.

3. The Carlyle group purchases *FCX* Performance, Inc from Barings for an undisclosed amount in October 2012.
4. In January 2013 *OMERS* purchased *Enwave Energy Corp* (an energy company) for $490mil from *The Carlyle Group*.
5. In February 2013, *OMERS* purchased *A.S.A.P. Industries Manufacturing, Inc.* (an energy company) for an undisclosed amount from *BARINGS*.

The above iterations provide insights into the relationships that develop through PE firms along time via transactions. Furthermore, it shows the way PE firms access capital and investments in proximate sectors: both *EQT* and *The Carlyle Group* owned companies in the energy sector and operationally engineered those companies. Once they improved the efficiencies of those companies — they sold their holdings to *OMERS* (a public pension fund endowed with an investment objective of receiving steady income). In Fig. 3 we capture the network of PE transactions. A black bold (respectively, red dotted) line indicates a transaction between two PE firms in 2012 (respectively, 2013). To understand network distance, we compute network matrices $\boldsymbol{A}_{2012}$ and $\boldsymbol{A}_{2013}$ such as

$$\boldsymbol{A}_{2012} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \qquad \boldsymbol{A}_{2013} = \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{pmatrix}.$$

We can then obtain distance matrices $\boldsymbol{D}^k_{2012}$ and $\boldsymbol{D}^m_{2013}$, $k, m = 1, 2, \ldots, n$. For example, distance $k = 1, 2, 3$ relative to the transaction structure in $\boldsymbol{A}_{2012}$ are given by

$$\boldsymbol{D}^1_{2012} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \qquad \boldsymbol{D}^2_{2012} = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

$$\boldsymbol{D}^3_{2012} = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix},$$

where by definition $\boldsymbol{D}^1_{2012} = \boldsymbol{A}_{2012}$. Similar distance matrices can be constructed for the network $\boldsymbol{A}_{2013}$. Indeed, for this specific example no triangular structures are present in neither $\boldsymbol{A}_{2012}$ nor $\boldsymbol{A}_{2013}$.[31]

4.2. The PE network structure

In Fig. 4 we draw the structure of secondary buyout transactions taking place between PE firms in period 1999–2017 with respect to PE firms engaging in at least *two* transactions during this period. In the graph, firms are represented as nodes. A link between two nodes exists if at least one transaction of portfolio companies between each other realized. The size of each node is proportional to the number of links involving that node. We make several observations. First, the network is densely connected. Second, interactions between PE firms are asymmetric, with a group of firms engaging in many transactions and a majority of less active firms. Third, albeit firms in the data-set are potentially very heterogeneous across multiple dimensions, we notice the apparent lack of separated "communities" (i.e. groups of tightly connected firms with limited cross-group connectivity). In particular, it appears that larger firms are homogeneously nested in the larger layer of smaller firms. This is coherent with our discussion on the shape of the distribution of partners' linkages in the previous section: as the distribution of transactions is more spread-out than the one of partners' transactions, we expect the majority of firms to be connected with firms of similar or smaller connectivity. This latter regularity can be indicative of the absence of the so called "core–periphery" structure which characterizes other financial contexts (see for an example on the inter-bank network Soramäki et al., 2007), where a majority of less active firms (the periphery) is connected to a small number of interconnected and very active firms. A possible explanation for the relatively balanced structure observed in the picture is that the majority of firms may have an incentive to favor relations with firms they share one or multiple partners with, or in other words, firms favor *transitive* transactions.

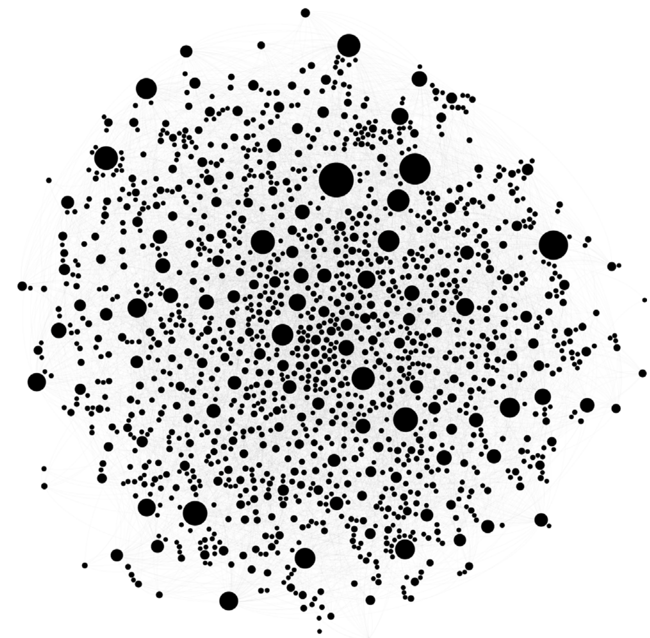

Fig. 4. The structure of secondary buyout transactions between all PE firms with at least two transaction in period 1999–2017. PE firms are represented as nodes (black-colored). The size of a node reflects the total number of the node's transactions. A link (gray-colored) between two nodes exists if at least one transaction of portfolio companies realized between each other.
Source: FactSet.

In Table 4 we explore the latter observation by comparing several network metrics constructed for the 1993–2017 PE structure with the ones generated for a Poisson random network calibrated on the average connectivity of the empirical structure. First, we notice that the PE network is characterized by roughly *ten times* the number of transitive deals expected in a random network, despite roughly expressing *half* of its transactions. We also point out that although most of transitive deals are generated by the 10% most active firms, a large fraction of less active firms are involved, as reflected by the positive median. To better understand the apparent balancedness of the structure, we consider two measures of centrality, *Closeness* and *Eigenvector* centrality (see Jackson, 2010b). These provide alternative measures of network distance between any PE firm and all the other firms in the network. The former one is the average length of the shortest path between the node and all other nodes in the graph. The more central a node is, the closer it is to all other nodes. For the PE network, this measure is relatively flat across nodes signaling that network components are tightly connected among each others, whereas for the random network, the presence of multiple separated components prevents the computation of the measure. Eigenvector centrality is a measure of the influence of a node in a network. The idea is that the centrality of a node is proportional to the sum of the centrality of its neighbors (Jackson, 2010b). A balanced network is indeed expected to show homogeneous

[31] Notice that the network of all transactions $\bar{\boldsymbol{A}} \equiv \boldsymbol{A}_{2012} + \boldsymbol{A}_{2013}$ is characterized by two triangles, $T_{1,2,3}$ and $T_{1,3,4}$.

Table 4
The table provides several network-based indicators for the 1999–2017 PE network and for a representative Poisson random network calibrated on the average degree of the empirical PE network.

PE network (1999–2017)	Total	Mean	Std. Dev.	Min	Median	Max
Transactions	7613	6.8	12.768	1	3	172
Transitive deals	3049	1.54	7.45	0	1	155
Closeness		0.272	0.037	0.156	0.273	0.405
Eigen. Cent.		0.010	0.019	0	0.004	0.208
Random network	Total	Mean	Std. Dev.	Min	Median	Max
Transactions	15,132	6.8	2.70	0	7	20
Transitive deals	434	0.02	0.07	0	0	1
Closeness		0	0	0	0	0
Eigen. Cent.		0.019	0.008	0	0.019	0.051

Table 5
The table presents the estimation results of the model in (2), where the probability for a mediocre investment to realize, $Outcome_{k,i,t} = 1$ is regressed against a standard continuous performance measure, the company-level terminal value (TEV), computed from the day of entry to the date of exit, for several truncations of the dataset. Truncations are constructed by removing deals characterized by a TEV below the $\kappa = 1\%$ to $\kappa = 60\%$ lowest percentile of the TEV distribution.

κ	1%	10%	20%	30%	40%	50%	60%
ξ_1	−0.00006	−0.00055	−0.00084	−0.00095	−0.0011	−0.00157	−0.00205
P-value	0.287	0.05	0.035	0.033	0.031	0.026	0.039

centralities across firms.[32] Albeit the two networks have comparable average eigenvector centralities, the random network centralities are roughly normally distributed, whereas the PE network is right-skewed, with a relatively high maximum eigenvector centrality to signal the presence of influential nodes.

4.3. Measuring transitive deals, performance and clique premium

Triangles, as defined in Section 4.1, are the immediate analytical representation of transitive deals. Given three firms $i, j, k \in N$, a triangle $T_{ijk,t}$ is defined as $T_{ijk,t} \equiv a_{ij,t} \times a_{jk,t} \times a_{ik,t}$, whereby $T_{ijk,t} = 1$ (respectively, $T_{ijk,t} = 0$) means that the triangle exists (respectively, does not exist). While in theory triangle is the correct statistics to capture transitivity, it may lead to degeneracy in estimation of network formation models.[33] To address such issue, in our model of network formation (see Section 4.4.1) we instrument triangles with the so called *geometrically weighed edgewise shared partner* (GWESP) statistics (Hunter et al., 2008), defined as

$$\Gamma_\alpha\left(\sum_{i<j<k} a_{ij}a_{jk}a_{ki}\right), \tag{1}$$

where α is a parameter. In words, $\Gamma(\cdot)$ is the weighted sum of the number of connected PE firms having exactly i shared partners weighted by the geometric sequence $(1-e^{\alpha})^i$, where α is the decay parameter.[34] We favor this simple statistics over triangles as the former is robust to the above degeneracy.

To understand the determinant and the prevalence of transitive deals it is necessary to supply a measurement of PE firm skill and, related, of investment performance. In fact, PE skills can be heterogeneous (Hochberg et al., 2007) and this may bias PE decision making. More importantly, while profit optimization is the long-run objective of rational PE firms, it is possible that instantaneous profit is only one of the factors driving the decision making process. In particular, following our Hypothesis 2.3, it can be that after controlling for PE firm skill, two equally performing PE firms A and B may be willing to forgo a fraction of instantaneous profits or to accept a less than optimal deal if the deal is conductive of repeated and more profitable trades in future resulting from, for example, better interconnection and information diffusion (see Hypothesis 2.4). To address these points, we include a measure of deal-level performance, $Outcome_{i,k,t}$, where k refers to the transacted company, t indicates the time of the deal and i is the PE firm. This is standard and directly collected from the *FactSet* dataset. An investment is *profitable* if the underlying company is exited via any channel other than bankruptcy,[35] and exit takes place within 11 years from acquisition. In other words, we treat late exits as a sign of mediocre investment (Arcot et al., 2015).

Such measure of performance is parsimonious and motivated by a sample preservation criterion as opposed to alternative metrics which require more company-level information, thus limiting the sample size and the power of our tests. Nonetheless, in Table 5 we correlate our binary performance measure against a popular alternative metrics: the company-level terminal value (TEV) computed from the day of entry to the date of exit (see, for example, Arcot et al., 2015), using all the $\hat{N} = 1201$ trades for which this indicator can be computed. We do so by estimating a simple probit model

$$P_\kappa(Outcome_{k,i,t}) = \Phi_\kappa(\xi_0 + \xi_1 TEV_{k,i,t}), \tag{2}$$

where $P(\cdot)$ is the probability of our indicator $Outcome_{k,i,t}$ to take value 1, $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution and the parameters ξ_0 and ξ_1 are estimated via a standard log likelihood procedure. As a robustness check against potential non-linearities, the regression is run on several truncations of the $\hat{N}$ dataset. Truncations are constructed by removing deals characterized by a TEV below the $\kappa = 1\%$ to $\kappa = 60\%$ lowest percentile of the TEV distribution. From the table, it appears that the coefficient ξ_1 is always negative (as expected) and significant at least at the 5% level for truncations above $\kappa > 1\%$.

We use investment performance to explicitly measure PE firms performance and thus clarify the determinant of decision-making. In the literature, measures of skill are generally interconnected to fund performance. For example, Kaplan and Schoar (2005) attribute persistent fund returns to manager skill. Hochberg et al. (2007) show that

[32] Notice that very inter-connected firms are not necessarily the most "central" ones. Suppose for example a PE network populated by multiple groups of PE firms such that for each group, only one firm (i.e. the "hub") is linked to firms of different groups. Intuitively, hubs are indeed more "central", relative to other firms. However, if hubs have few links relative to other firms, connectedness and centrality can diverge.

[33] In particular, the inclusion of triangles in network formation models may give rise to graphs that are artificially either complete, or empty, or have edges concentrated in a small subset of the graph (Hunter et al., 2008).

[34] The transformation is also known as *curved triangle*, as it provides a smoothing of the original notion (see Hunter & Handcock, 2006). In untabled calibrations we find $\alpha = 0.2$ to be optimal.

[35] That is, via secondary buyout, IPO or Trade Sale (either public or private).

the proportion of successful deal outcomes are representative of fund returns. Since our study focuses on individual deals rather than fund performance, we follow Stanfield (2019) and use a skill measure that is allowed to dynamically evolve based on PE firm's past performance. More specifically, we will flag a PE firm as low skill if it incurred in at least one non-profitable investment in the previous four years.[36] Indeed, this measure of performance dynamically trails through the dataset and the same PE firm may switch from low skill to high skill and viceversa depending on the performance of the underlying investments realized within a four-year window. This strategy produces, for each PE firm, a set of performance evaluations which we operationalize to construct a measure of firm's skill relative to the performance of other firms in the dataset (see the definition of variable $skill$ in Section 4.4.2).

The performance measures are operationalized to explore the existence of a clique premium in PE firms behavior. This requires us to focus on performance of transitive deals between firms characterized by a history of such type of deals. More precisely, a clique premium (respectively, *malus*) can be established by measuring the performance of any trade generative of a *new* triangle (as it is the case of Trade 4 in Example 4.1) as opposed to the performance of trades generating triangles between firms already endowed with transitive deal with each other, controlling for firms performance. A major issue can bias the comparison of the performance of newly established triangles with the one of repeated triangles. Suppose that newly established triangles are conductive of less profitable trades with respect to future trades. This can be either due to firms trading upon the expectation of a clique premium, or simply because if a newly triangular trade is not profitable, there will not be future trades between those PE firms. We resolve the bias by generating several variables related to transitive deals aiming at isolating the performance of *newly established triangles which will lead to future triangles* against, generically, the performance of repeated triangles,[37] under a rolling-window period of 4 years period. Indeed, a strong argument in favor of the existence of clique premium would be either negative or non significant positive profits for triangles leading to new triangles in future, implying that PE firms are willing to incur in the potential loss (or insignificant gains) of having bad deals if these lead to gains from repeated interaction.

4.4. Empirical models

4.4.1. PE network formation

Motivated by the empirical regularities of Sections 2 and 4.2, we explore the core idea of our paper, that is PE firms leverage their network to establish future links, and such behavior is only partially driven by homophily (Hypotheses 2.1 and 2.2). To address this idea, we build models of network formation in which agents condition their decisions on the *structure* of transactions as well as firm-level and homophily controls. As other contemporary works on formation of financial networks, we acknowledge that connections between firms are not independent (see for example Stanfield, 2019). Hence, the traditional logit and probit approaches in which the likelihood of a new inter-firm link depends only on individual incentives may deliver biased estimations.

To estimate our models of network formation, we use Exponential Random Graph Models[38] (ERGMs). These are multivariate maximum likelihood regressions which allow for simultaneous dependence relations between all nodes in a network (Ahern & Harford, 2014). In particular, these models allow us to quantify the incidence of *transitive* connections in the decision of firms to create links. The basic idea is that an ERGM specifies a vector of sufficient statistics (such as links and triangles) and economic covariates and then formulates the probability of observing the network as depending on the count with all networks with the same sufficient statistic value being drawn with equal probability conditional on the economic covariates. The key difference between ERGM and a common limited-dependent variable model such as a logistic regression is that the objective function of the maximization problem in a common logistic regression is a single outcome variable, whereas in ERGM, it is an entire network (Ahern & Harford, 2014). For this part of the analysis, we construct a static version of the PE network. Let $\bar{\boldsymbol{A}} = \min\left\{\boldsymbol{A}_{1999} + \cdots + \boldsymbol{A}_{2017},\ 1\right\}$ with the associated matrix of economic homophily covariates $\bar{\boldsymbol{X}} = (1/T)\sum_{t=1}^{T} \boldsymbol{X}_t$ (described below). Also, let $\boldsymbol{S}(\bar{\boldsymbol{A}})$ denote the matrix of network characteristics we are interested into, that is links and the *GWESP* as discussed in Section 4.3

$$\boldsymbol{S}(\bar{\boldsymbol{A}}) \equiv \left(\sum_{i<j} a_{ij},\ \Gamma_\alpha\left(\sum_{i<j<k} a_{ij}a_{jk}a_{ki}\right)\right),$$

such that $\Gamma(\cdot)$ is precisely the *GWESP*. Then, the ERGM specifies the probability $P(\cdot)$ of observing a network $\bar{\boldsymbol{A}}$ endowed with network attributes $\boldsymbol{S}$ conditional on covariates $\bar{\boldsymbol{X}}$ such as[39]

$$P_\beta(\bar{\boldsymbol{A}}|\bar{\boldsymbol{X}}) = \frac{\exp(\beta \cdot \boldsymbol{S}_{\bar{X}}(\bar{\boldsymbol{A}}))}{\sum_{\bar{A}'}\exp(\beta \cdot \boldsymbol{S}_{\bar{X}}(\bar{\boldsymbol{A}}))} \tag{3}$$

where the denominator is a normalizing constant computed on all possible networks[40] and $\boldsymbol{\beta}$ is the vector of parameters to be estimated. Computation of the normalizing constant is computationally impossible due to the size of the set of possible interactions. Hence, following standard practice we use Markov chain Monte-Carlo (MCMC) methods. As illustrated by Ahern and Harford (2014), the idea behind MCMC methods is to create a Markov chain on the set of nodes in $\bar{\boldsymbol{A}}$, where the equilibrium distribution equals $P_\beta(\bar{\boldsymbol{A}}|\bar{\boldsymbol{X}})$. Once the equilibrium distribution is reached through the iterative procedure, random draws can be computed for m observations of $\bar{\boldsymbol{A}}$ necessary to maximize an approximate log-likelihood function attached to[41] (3).

Regressors in $\bar{\boldsymbol{X}}$ are described in Appendix. To control for homophily we include proxies relative to each PE firm's head-quarter region, primary sector and dominant entry-exit strategies (See Section 3). The Region a PE firm is head quartered can impact via a *home bias* the likelihood of secondary buyouts between PE firms in the same region (Coval & Moskowitz, 1999). Through a similar mechanism, also sectoral proximity can favor PE firm deals (Cartwright & Schoenberg, 2006). Homophily can be also observed in the strategic behavior of PE firms, reputation and size. Achleitner and Figge (2014) bring evidence that PE firms are likely to use the same strategies to enhance value in portfolio companies, even after a secondary buyout. We address firm's size and reputation[42] respectively by number of funds and PE firm age. Kaplan and Schoar (2005) show that performance of PE funds is time persistent and this can be attributed to PE firm's growing experience and skills in selecting, restructuring, and monitoring target

[36] In untabled analysis we also tested a continuous measure of skill constructed by taking the fraction of non-profitable over profitable investments. We also tested alternative rolling windows and confirmed the results for 3 and 5 years.

[37] Precisely, triangles can be partitioned into the following set: { (*newly established triangles leading to triangles in the next 4 years*), (*newly established triangles not leading to further triangles in the next 4 years*), (*repeated triangles*) }.

[38] These are among the most widely used models of network formation. For a primer on the econometrics of ERGMs, see the excellent reviews by Graham (2015) and Chandrasekhar (2016) or Online Appendix III of Ahern and Harford (2014).

[39] It is easy to show that when the sufficient statistics $\boldsymbol{S}(\bar{\boldsymbol{A}})$ is given by links, or in other words, links are independent and $\boldsymbol{S}(\boldsymbol{A}) \equiv \sum_{i<j} a_{ij}$, the ERGM coincides with a logit model with dependent variable corresponding to $\bar{\boldsymbol{A}}$.

[40] Although ERGMs models are reduced-form specifications, it is possible to construct utility-based microfoundations (see, for example, the model of Mele, 2017).

[41] Practically, we implement our estimation via the *Statnet* Python suite available through http://statnetproject.org.

[42] See, for evidence and motivation of homophily in these two dimensions, Demiroglu and James (2010).

Table 6
Characteristics of the deal data from the FactSet data-set described in Section 3 with mean, standard deviation and main percentiles of numerical control variables used in the empirical analysis. *SBO* is a binary variable indicating whether the deal was exited via a secondary buyout. *Fund age* indicates the age of fund participating to the transaction at the time of the transaction. *Skill* is a binary variable picking value of 1 if the PE firm was involved in at least one non-profitable investment in the previous four years, where a profitable investment is an investment exited within 10 years with any means other than bankruptcy of the underlying investment. *Number of years held* indicates how many years a PE firm has held the underlying investment. *Centrality* is constructed upon the eigenvector centrality λ (see Section 4.2 for a description) of each PE firm. Variable *NewT* (*RepT*) picks value 1 if a deal k expands (respectively, does not expand) the size of *at least* one clique j (see Section 4.3) and 0 otherwise. Lastly, variable $FirstOfRepTri_{k,i,t}$ is a dummy taking value of 1 if a deal between PE firms establishes a clique which will result in further cliques in the future.

	Mean	S.D.	1%	25%	50%	75%	99%
SBO	0.10	0.29	0	0.1	0	0	1
Fund age	26.62	19.98	4.00	16.00	22.00	31.00	119.00
Skill	0.39	0.49	0	0	0	1	1
Number of years held	5.48	3.91	0.17	2.56	4.66	7.59	17.74
Centrality	0.03	0.04	0	0	0.01	0.03	0.20
NewT	0.07	0.26	0	0	0	0	1
RepT	0.46	0.50	0	0	0	1	1
FirstOfRepTri	0.07	0.25	0	0	0	0	1
Observations	88,467						

Table 7
Characteristics of the deal data from the FactSet data-set described in Section 3. Count of PE exit strategy (rows) versus investment length (columns). SBO is as defined in Table 6.

	Exit ≤ 11 years	Exit > 11 years
SBO	8432	552
Other Exit	73,850	11,320

firms. On the other hand, size can also bias transaction-making via “diseconomies of scale” (Lopez-de Silanes et al., 2015).

Lastly, in Table 7 we put the SBO deals in relation to performance, as measured in terms of investment length. We notice that in our dataset, only a small fraction of SBOs are exited after 11 years.

4.4.2. Clique premium

Having isolated the relevance of transitive deals in PE decision-making we turn to establishing the economic determinants of transitive deals. To do so, we construct a binomial logit model for understanding the probability of *unprofitable* deals, $P(Outcome)$. As stated in Section 4.3, an unprofitable outcome is a deal that either has been exited with bankruptcy, or it is plagued by late exit[43] (i.e. it has been exited no earlier than 11 years from acquisition).

$$\begin{aligned} P(Outcome_{k,i,t}) = f(\ & \beta_0 + \beta_1 SBO_{k,t} + \beta_2 Skill_i + \beta_3 \lambda_{i,t} + \boldsymbol{\phi} \cdot \boldsymbol{X}_i \\ & + \beta_4 NewT_{k,i,t} + \beta_5 RepT_{k,i,t} + \beta_6 NewT_{k,i,t} \times RepT_{k,i,t} \\ & + \boldsymbol{\iota} \cdot \boldsymbol{\theta}_{k,i,t} \\ & + \beta_7 FirstOfRepTri_{k,i,t} + \beta_8 FirstOfRepTri_{k,i,t} \\ & \times Skill_{i,t} + \boldsymbol{\psi} \cdot \boldsymbol{\tau} + \epsilon\ ), \end{aligned} \tag{4}$$

where k refers to the transacted company, t indicates the time of the deal and i is the PE firm. Deal level controls are in the first line of (4). Coherent with Stanfield (2019), to measure PE firm skill, we construct the distribution of unprofitable deals at PE firm level and define a binary indicator $Skill_i$ which picks value 1 for firms located below the 10th percentile in such distribution.[44] We also control for the firm-specific controls $\boldsymbol{X}_i$ described after (3). To better control for firm's positional reputation (Demiroglu & James, 2010), we also include the firm's network centrality, captured by its eigenvector centrality $\lambda_{i,t}$ (see Section 4.2). To study clique premium, we introduce binary regressors for triangles, discriminating between newly established triangles and triangles formed between firms belonging to established triangles (see Section 4.3). More precisely, dummy $NewT$ ($RepT$) picks value 1 if deal k expands (respectively, does not expand) the size of any existent clique for *at least* one of the PE firms involved and 0 otherwise. We put cliques in relation to SBOs by including in (4) the full factorial of variables $SBO_{k,t}$, $NewT_{k,i,t}$ and $RepT_{k,i,t}$. Critical to our results, we also control for cliques between firms which will result in further cliques, $FirstOfRepTri_{k,i,t}$ and the interaction between such variable and firm's skill (see the discussion at the end of 4.3). Lastly, in (4), $\boldsymbol{\theta}$ is an interaction vector between variables SBO, *NewT* and *RepT* and τ contains linear and exponential time trends (Arcot et al., 2015).

Table 6 summarizes information on variables used in baseline model of Section 4.4.2. Out of the 88,467 deals available in the data-set, about 10% of all deals are exited through secondary buyout. Funds are relatively mature (Arcot et al., 2015), with almost 40% of them exiting invested firms within 10 years with means other than bankruptcy of the underlying investment. Important for our analysis, by looking at the constructed binary variables $NewT$ and $RepT$, we note that around 7% of deals expand existing cliques for at least one of the firms involved in the transactions, whereas 47% of deals do not. This is consistent with the geometrical structure of the PE network discussed in Section 4.2 and with data of Table 4, where we benchmark the realized PE network against a random structure.

4.4.3. Information diffusion

Lastly, we investigate whether inter-firm relationships underlying the structure as driven by clique premium affect information diffusion, or in other words, we ask whether information diffusion can be a component of the clique premium. We allow our models to capture the dynamic nature of information diffusion (Shiller & Pound, 1989 and Jackson, 2014) under the following dimensions. First, relationships can decay in *time* (Hochberg et al., 2007). Hence, we assume an inter-firm connection between two firms i and j is “active” in year t if the two firms engaged in at least one trade in the previous five years. To do so, we construct a 5-years trailing transaction window in the spirit of Hochberg et al. (2007). Second, for every year t, we allow relationships to decay in *space* as advanced in Hypothesis 2.4. In other words, the likelihood for a firm i to engage in a transaction is correlated with the transaction decisions of firm j, with correlation decaying as a function of the distance between i and j, where distance is as defined in Section 4.1. To capture the former dimension, we construct a dynamic network $\hat{\boldsymbol{A}}_{t,q}$ based on a $q = 5$ year rolling window. The window captures the transitory nature of relationships between PE firms (e.g. if

[43] Such measure is strongly correlated with the actual funds returns (Kaplan & Schoar, 2005), see the discussion and a benchmark against an alternative popular deal-level performance measure in Section 4.3.

[44] In untabled analysis we confirm results are unaffected for thresholds at 1th, 5th, 15th percentile.

Table 8
ERGM model describing the probability of transaction (a binary variable taking value 1 for transacting firms and 0 otherwise) for any of the PE firms belonging to the PE Network described in Section 4.2. Variables are described in Appendix. *Connections* tests the likelihood for two PE firms to engage in a SBO conditional on having engaged in SBO in the past. *GWESP* tests the likelihood for PE firms belonging to a clique (see Section 4.3) to engage in further deals. This is a univariate statistics with a parameter α calibrated to $\alpha = 0.2$ to let the statistics coefficient approximate the odds ratio of link formation between two firms sharing at least one PE partner. It is an unbiased proxy for the average number of transitive deals. *Amount of funds* measures the size of a PE firm (in USD millions). *Years of experience* indicates the difference between 2017 and the year in which the PE firm i has been established. *PE Type* is a binary variable constructed using Primary SIC Divisions. It takes value 1 (respectively, 0) if the corresponding PE firm is a *financial engineer* (respectively, *operational engineer*). These categories depend on strategy PE firm uses to promote her fund, as discussed in Section 2. *Region* is a categorical variable corresponding to either of seven macro-geographic areas. *Sector* is a categorical variable corresponding to either of ten SIC macro-divisions. Coefficients are reported in log-odds. stmsymbol *, ** and *** represent statistical significance at 0.1, 0.05 and 0.01 level, respectively.

	(1)	(2)	(3)	(4)	(5)
Connections	−5.785***	−6.360***	−6.700***	−7.103***	−6.999***
	(0.0115)	(0.0156)	(0.0213)	(0.0249)	(0.0266)
GWESP		1.433***	1.053***	1.371***	1.365***
		(0.0164)	(0.0199)	(0.0169)	(0.0170)
Amount of funds			0.022***		−0.769***
			(0.0008)		(0.0454)
Years of experience			0.005***		−0.102**
			(0.0003)		(0.0695)
PE Type				0.499***	0.479***
				(0.0212)	(0.0224)
Region				0.690***	0.689***
				(0.0207)	(0.0196)
Sector				0.464***	0.465***
				(0.0274)	(0.0285)
PE firms	2230	2230	2230	2230	2230
Transactions	7613	7613	7613	7613	7613

two PE firms transacted in 2001 and did not transact any further, in 2006 their link would be dissolved). Formally, let h and t be two generic years and let $\hat{\boldsymbol{A}}_{t,q}$ be a $n{\times}n$ matrix with generic entry $\hat{a}_{ij,t,q} = 1$ if $a_{ij,h} = 1$ such that $t - h \leq q = 5$. Then, matrix $\hat{\boldsymbol{A}}_{t,q}$ tracks the time evolution of the network structure. To capture the space dimension mentioned above, we include the distance matrices $\hat{\boldsymbol{D}}^{k}_{q,t}$, $k \leq 3$ associated[45] to the dynamic network $\hat{\boldsymbol{A}}_{q,t}$. The construction of time-decaying links motivates our preference for ERGM in the present setting as opposed to temporal exponential random graph models (as in Stanfield, 2019), as in the latter the network structure is posited and fixed, equivalent to a zero decay factor. The hypothesis that firms decide whether to engage in transactions conditional on the structure of past transactions is endogenous, as the outcome variable is on both sides of the estimation equation. Similar to Stanfield (2019), we address potential endogeneity inherent to estimating a transaction architecture with measures built on it by imposing a one year gap between estimated transaction architecture and the historical transaction structure. Moreover, as a firm's position in the network determines the firms' exposure to the activity of her own neighbors and the firm itself, network position may indeed confound the role of neighbors' activity. We control for the effect of centrality by augmenting the model with the vector of Eigenvector centralities of all PE firms λ, similar to (4). The dynamic ERGM we design to capture information diffusion is given by

$$P(\hat{\boldsymbol{A}}_{5,t+1} \mid \bar{\boldsymbol{X}}, \lambda, \hat{\boldsymbol{D}}^{1}_{5,t}, \hat{\boldsymbol{D}}^{2}_{5,t}, \hat{\boldsymbol{D}}^{3}_{5,t}) = \frac{\exp(\boldsymbol{\beta} \cdot \boldsymbol{S}_{\bar{X}}(\hat{\boldsymbol{A}}) + \delta \cdot \lambda + \gamma_1 \hat{\boldsymbol{D}}^{1}_{5,t} + \gamma_2 \hat{\boldsymbol{D}}^{2}_{5,t} + \gamma_3 \hat{\boldsymbol{D}}^{3}_{5,t})}{\sum_{\hat{A}'} \exp(\boldsymbol{\beta} \cdot \boldsymbol{S}_{\bar{X}}(\hat{\boldsymbol{A}}) + \delta \cdot \lambda + \gamma_1 \hat{\boldsymbol{D}}^{1}_{5,t} + \gamma_2 \hat{\boldsymbol{D}}^{2}_{5,t} + \gamma_3 \hat{\boldsymbol{D}}^{3}_{5,t})}, \tag{5}$$

where $\bar{\boldsymbol{X}}$ is the matrix of covariates defined in Section 4.4.1 and λ is defined above.

4.4.4. Addressing endogeneity concerns

The decision of firms of whether to engage in new deals conditional on the structure of past transactions is endogenous, as the outcome variable is on both sides of the estimation equation. This raises potential endogeneity concerns that cascade in the test structure of all hypotheses considered in our work. An instrumental variables approach controlling for the transaction decision is difficult due to the lack of ideal instruments (see Stanfield, 2019, Brander et al., 2002, and Cumming & Walz, 2010 for a discussion). We address such concern by explicitly accounting for the network structure of the transaction layer in two complementary ways. First, in the pairwise decision model in (4), we adopt a battery of geometrical covariates and centrality measures to control for endogeneity at clique level and network level, respectively. Second, for network formation models in (3) and (5), we solve the issue by deciding to use a ERGMs modeling approach, which explicitly accounts for all possible network structures taking place between firms. As noted by Ahern and Harford (2014), ERGM estimation provides key benefits over decision analysis between individual firms in isolation. In particular, by considering the entire layer of PE firms transactions, ERGM alleviates selection bias caused by only considering firm pairs directly involved in deals. The network approach explicitly accounts for dependencies between all firms, including higher order connections, and allows for tests of the propagation of firm-level shocks from one firm to another across the entire network. To address potential residual endogeneity concerns inherent to estimating a dynamic transaction architecture with measures built on it, in our analysis of the dynamic model in (5) we impose a one year gap between estimated transaction architectures and the historical transaction structure (Stanfield, 2019) and we augment the model to also include a static measure of centrality built upon the entire sample period.

5. Results

5.1. Network formation

In this section we estimate the model in (3) to test whether PE firms leverage their existing connections to establish new transactions, controlling for *homophily* (Hypothesis 2.2). Estimation results are reported in log-odds format in Table 8. Columns (1) and (2) test the probability for two PE to transact with each-other conditional only on the matrix of geometrical characteristics $\boldsymbol{S}(\bar{\boldsymbol{A}})$ described in Section 4.4.1 whereas Columns (3)–(5) introduce a battery of homophily controls relative to PE firms' size (in terms of number of funds under management), years

[45] In untabulated regressions we shows that the decaying nature of information holds at distances $k = 4, 5$.

of experience, dominant entry-exit strategy, head-quarter region and primary sector (see Section 3). We make two observations. First, we notice that the probability of transacting is negatively and significantly affected by past transactions across all specifications, opposite to other papers such as (Stanfield, 2019). For example in Column (1), where we test a model where links are formed entirely at random, we obtain that the only coefficient (i.e. the intercept *Connections*) gives a log-odds of -5.785, corresponding to a linkage probability of 0.31%. This is indeed consequential of the relatively sparse nature of the PE network, where each PE firm is in fact linked to only 6.8 firms, on average. Second, the opposite observation holds for the triangle proxy *GWESP*, whose marginal increase significantly rises the probability of further links across all specifications by an odds-ratio factor ranging between 2.866 and 4.193. Taken together, these observations are consistent with our discussion of Section 4.2: albeit firms in the data-set are potentially very heterogeneous across multiple dimensions, "communities" (i.e. groups of tightly connected firms) are not separated, one reason being that firms leverage their existing connections to establish new connections. In Column (5) we estimate the full specification of the model in (3) containing our homophily controls (see Section 4.4.1 for a description and reference to extant literature). Importantly, we observe that the additional presence of homophily controls — all significant[46] between 1% and 5% - only marginally affects the strength of the positive coefficient of *GWSP*. In fact, when homophily matrix $\boldsymbol{X}$ is included in the model, the coefficient scales from a odds-ratio factor of 4.19 as estimated in the model containing only geometrical regressors of Column (2), to a factor of 3.92, thus confirming Hypothesis 2.2. By computing marginal probabilities from the odds-ratio of full model in Column (5), we observe that joining a clique increases chances of forming further links on average by 2.8 times. This may consistently motivate why in the PE network we observe secondary buyouts clustering around a *core* of PE firms (see Section 4.2)

5.2. Clique premium

Table 9 contains logit estimates (in odds ratio format) for the clique premium formulated in Hypothesis 2.3 (Section 2) on the ground of the model described in Section 4.4.2. Out of the $k = 78{,}482$ transactions contained in the *FactSet* data-base, we restrict our attention to period between 1991:Q1 and 2020:Q1 (see Section 4.2 for a granular description of the data). For each of the surviving $N = 63{,}445$ transactions we analyze the likelihood for a deal to produce an unprofitable outcome, that is a deal that is either exited via bankruptcy or later than 11 years from acquisition (see Section 4.4.2 for details). The logit models are estimated with deal-clustered standard errors robust to heteroskedasticity. The dependent variable $Outcome$ picks value 1 if the deal is unprofitable and 0 otherwise. In the table, Column (1) is the benchmark case where the probability of default is conditioned only for PE firm homophily controls $\boldsymbol{X}$ and the deal being a secondary buyout (SBO). Column (2) tests the additional effect of PE firm skill, whereas Column (3)-(6) introduce a battery of geometrical relationships to single out the existence of a clique premium. To circumvent concerns of multicollinearity between *Skill* and network measures, (5) replicates the full model of column (6), corresponding to (4), with the only omission of the vector of geometrical interactions $\boldsymbol{\theta}$.

For all specifications, we find that higher skill of PE firms and use of SBOs reduces the odds of a bad outcome, by a factor of $0.54 - 0.62$. The literature on SBOs performance is ambivalent. For example, while for Achleitner and Figge (2014) and Degeorge et al. (2016) there is no difference in profitability between primary and secondary deals, Bonini (2015), Sousa (2010) and Wang (2012) find lower operating performance in SBOs (see also Arcot et al., 2015 Degeorge et al., 2016 for a discussion of profitability of SBOs).

By comparing the coefficient of centrality across (3)-(6), we observe a strong and persistent reduction in the odds of a bad outcome for transacting PE firms that are more central in the PE network, in a factor range of $0.009 - 0.017$. Importantly, controlling for PE firm's size and age moderates by only 0.76% the centrality factor. Indeed, while this result is supportive of Hypothesis 2.3, centrality does not account for the potential heterogeneity of cliques underlying the network structure. In Column (4) we isolate the anatomy of cliques by comparing coefficients $NewT$, $RepT$ and their interaction, $NewT \times RepT$. We make three observations. First, we notice that the odds of a bad outcome in a transaction that does not expand the clique size for at least one of the PE firms involved is 0.73 times lower the alternative case and strongly significant, whereas the opposite is true for transactions that expand the clique size for at least one of the PE firms involved. Second, this latter effect is significant only at 10%, suggesting that $NewT$ is capturing conflicting behaviors. Third, we observe that the odds of a bad outcomes are 1.49 times higher when the interaction coefficient $NewT \times RepT$ is non-zero, and the effect is strongly significant. By combining these two latter observations, we confirm that a clique-expanding transaction does not increase odds of a bad outcome only if the transaction expands the clique of *all* the firms involved in it. In other words, the odds of a bad outcome are higher for transactions *amplifying* disparities in the clique structure of participating firms. This result may explain the conflicting evidence on performance of SBOs deals cited above. Our result is potentially supportive of agency-based theories attributing the source of SBOs' underperformance to disparities of market power: as less established PE firms are more likely to participate to a smaller number of (smaller) cliques than more established PE firms, a deal connecting a pool of heterogeneous PE firms would be captured by the interaction coefficient above.

A possible explanation for firms deciding to engage in clique-expanding transactions at a cost of a bad outcome is that firms are willing to forego short-term profit if the clique-expanding deal is conductive of repeated and more profitable trades in future. However, the comparison of the performance of newly established triangles with the one of repeated triangles can be biased. Suppose that newly established triangles are conductive of less profitable trades with respect to future trades. This can be either due to firms trading upon the expectation of a clique premium, or simply because if a newly triangular trade is not profitable, there will not be future trades between those PE firms. We resolve the bias in column (5)–(6) by adding variable $FirstOfRepTri$, isolating the performance of *newly established triangles which will lead to future triangles* against, generically, the performance of repeated triangles. From Table 9, we confirm that deals that carry heterogeneous effects of clique size reduce by a negligible factor the odds of negative outcomes (odds ratio of 0.98), confirming that the clique premium requires *multiple* interactions (so that each firm's clique size stabilizes) to become apparent, as the first interaction has higher odds to be at loss.

[46] In untabled regressions we disaggregate our homophily estimates. From *PE Type* we find that firms under *Financial Engineering* type are more likely to transact with themselves compared to PE firms under *Operational Engineering* type (see also Section 3). Both these results are statistically significant, and the magnitudes are economically meaningful. For example, for a financial engineering firm is twice as important to be transacting with another financial engineer compared to transacting with a PE firm that specializes in the same sector. Relatively to geographic areas, we find that *Africa* has an economically meaningful and statistically significant coefficient, at odds with behavior of *Latin America* and *Middle East*. This suggests that PE firm headquartered in Africa are more likely to be transacting with another PE firm headquartered in Africa, compared to firms located in Latin America or Middle East transacting with a firm in its own area. In other words, firms located in Latin America or Middle East are most likely to engage in cross-border transactions. Lastly, from disaggregated sectoral analysis, we find that PE firms focused in *Finance*, *Manufacturing* and *Services* sectors are more likely to transact with each other and the relationship is statistically significant.

Table 9
Estimates for the dichotomous logit model on clique premium in (4). The dependent variable *Outcome* takes value 1 if the deal was unsuccessfully exited by the PE firm and 0 otherwise. Results are in odds ratio. Variables *Skill×FirstOfRepTri* and *New×RepT* are the interaction between *Skill* and *FirstOfRepTri* and *NewT* and *RepT*, respectively. The vector of geometrical interactions and homophily controls, respectively given by θ and $\boldsymbol{X}$, are defined in Section 4.4.2. Symbols *,** and *** represent statistical significance at 0.1, 0.05 and 0.01 level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
SBO	0.536***	0.533***	0.574***	0.616***	0.555***	0.615***
	(0.0260)	(0.0255)	(0.0317)	(0.0656)	(0.0284)	(0.0708)
Skill		0.893***	0.893***	0.895***	0.898***	0.897***
		(0.0249)	(0.0247)	(0.0217)	(0.0215)	(0.0262)
Centrality			0.00994***	0.0175***	0.0170***	0.0175***
			(0.00343)	(0.00767)	(0.00594)	(0.00603)
NewT				1.090*	1.149***	1.090*
				(0.0544)	(0.0612)	(0.0511)
RepT				0.727***	0.716***	0.727***
				(0.0223)	(0.0195)	(0.0228)
NewT × RepT				1.489***	1.382***	1.490***
				(0.136)	(0.119)	(0.120)
FirstOfRepTri					0.928	0.929
					(0.0585)	(0.0602)
Skill × FirstOfRepTri					0.976	0.974
					(0.104)	(0.111)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Interactions θ	No	No	No	Yes	No	Yes
Controls $\boldsymbol{X}$	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63445	63445	63445	63445	63445	63445
Pseudo R^2	0.080	0.081	0.085	0.090	0.089	0.090

Table 10
Estimation table of the dynamic ERGM model in (5) relative to distance coefficients γ_k, $k = 1, 2, 3$. In the table, estimates are log-odds. The number in parenthesis under each estimate is the associated standard deviation. Symbols *,** and *** represent statistical significance at 0.1, 0.05 and 0.01 level, respectively.

	2000/04	2001/05	2002/06	2003/07	2004/08	2005/09	2006/10
γ_1	3.03***	2.74***	1.96***	1.95***	1.92***	2.43***	2.23
	(0.37)	(0.21)	(0.21)	(0.17)	(0.16)	(0.13)	(0.13)
γ_2	1.35***	0.81***	0.58***	0.64***	0.93***	1.02***	0.68***
	(0.41)	(0.29)	(0.21)	(0.14)	(0.10)	(0.09)	(0.10)
γ_3	0.93**	−0.35	0.12	0.23***	0.47***	0.52***	0.35***
	(0.42)	(0.36)	(0.16)	(0.09)	(0.06)	(0.06)	(0.06)
	2007/11	2008/12	2009/13	2010/14	2011/15	2012/16	2013/17
γ_1	2.40***	2.51***	2.49***	2.39***	2.18***	2.33***	2.04***
	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)
γ_2	0.65***	0.78***	0.77***	0.74***	0.96***	0.93***	0.78***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.07)	(0.07)	(0.07)
γ_3	0.42***	0.42***	0.47***	0.53***	0.61***	0.62***	0.56***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)

5.3. Information diffusion

In Section 5.2 we considered investment performance and found that a clique premium exists in the context of repeated interactions between firms endowed with uniformly sized cliques. In this Section we argue that the PE network vehiculates information across PE networks. Therefore, the clique premium determines the pathways by means of which information diffuses across the network. In other words, information transmission may constitute a reinforcing mechanism for network formation. To investigate this, we test Hypothesis 2.4 by estimating the dynamic ERGM model in (5).

Table 10 collect estimation results in log-odds with associated standard errors. We make three observations. First, we notice that all distance coefficients γ_1, γ_2 and γ_3 (see Section 4.4.3) are strongly significant, implying that PE firms' trading decisions are affected by the actions of PE firms within a radius of distance[47] $k \leq 3$ in the PE network. Second, coefficients are unevenly spread: by converting log-odds in odds-ratio, we obtain a factor interval of 1.12–22.20, implying that neighbors' actions affect firms' decisions by a maximum of 22.20 times and no less than 12% against the base-line. Third, distance coefficients are positive, strongly significant and relatively stationary across years, implying that the effect of information diffusion is structurally stable across the data-set. This holds for all network windows with the sole exception of 2001–2005, in which distance parameter $\gamma_3 = -0.35$ is non-significant. All these observations confirm the first part of Hypothesis 2.4, that is PE firms more than one link away from a transacting firm have an increased likelihood to engage in secondary buyouts in the next period. Lastly, we notice that fixed the temporal window, distance coefficients are ordered according to $\gamma_1 > \gamma_2 > \gamma_3$ and such ordering holds for all temporal windows across the data-set. This validates the second part of Hypothesis 2.4, that is information decays with distance, or in other words, the increase in the likelihood to transact upon the transaction of neighbors falls in the network distance from the transacting firm.

In Fig. 5 we plot the estimated coefficients (in log-odds) and confidence intervals of distance coefficients $\gamma_k, k = 1, 2, 3$ of Table 10. Each point corresponds to the coefficient estimated using the dynamic ERGM model conditional on network structure $\hat{\boldsymbol{A}}_{t,5}$, such that a link between two PE firms i and j is present (i.e. element $a_{ij,t,5}$ of matrix $\hat{\boldsymbol{A}}_{t,5}$ is equal to 1) if at least one transaction between i and j has been observed

[47] In untabled results we show that the same dynamics carry over a $k \leq 5$ radius.

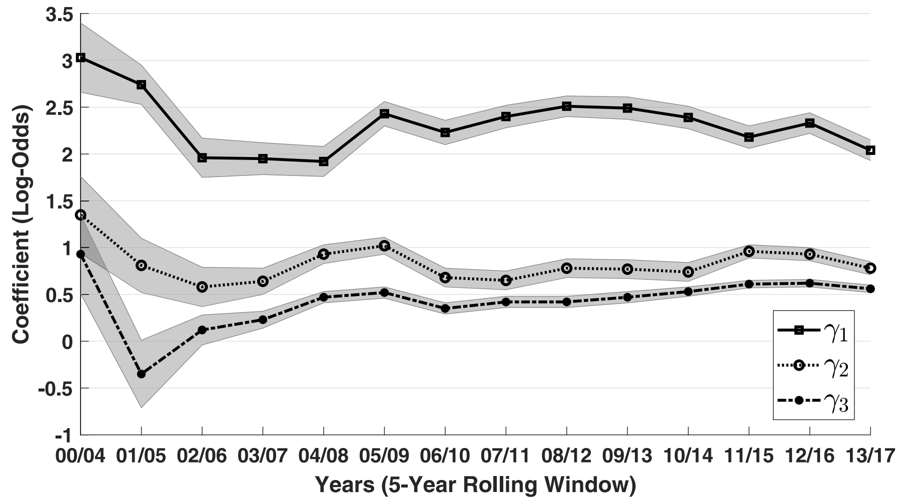

Fig. 5. The figure plots the estimated coefficients (in log-odds) and confidence intervals of distance coefficients $\gamma_k, k = 1, 2, 3$ for the dynamic ERGM model in (5). Each point corresponds to the coefficient estimated using the dynamic ERGM model conditional on network structure $\hat{\boldsymbol{A}}_{t,5}$, such that a link between two PE firms i and j is present (i.e. element $a_{ij,t,5}$ of matrix $\hat{\boldsymbol{A}}_{t,5}$ is equal to 1) if at least one transaction between i and j has been observed in years $t, t+1, \dots, t+4$, for $t = 2000, \dots, 2013$. The shadowed areas surrounding any estimate represent the associated confidence interval. The solid line connects estimates of γ_1 across years relative to covariate distance matrix $\hat{\boldsymbol{D}}_5^1$, whereas the dotted line and the dash-dotted line connect estimates of γ_2 and γ_3 relative to covariate distance matrix $\hat{\boldsymbol{D}}_5^2$ and $\hat{\boldsymbol{D}}_5^3$, respectively.

Table 11
Table of diffusion coefficients constructed from distance coefficients γ_k, $k = 1, 2, 3$. Diffusion coefficients are constructed from odds-ratio variations of parameter estimates of Table 10.

	2000/04	2001/05	2002/06	2003/07	2004/08	2005/09	2006/10
ρ_2	18.6%	14.5%	25.2%	27%	31.2%	24.4%	21.2%
ρ_3	12.2%	4.6%	15.9%	17.9%	23.5%	14.8%	15.3%
	2007/11	2008/12	2009/13	2010/14	2011/15	2012/16	2013/17
ρ_2	17.4%	17.7%	17.9%	19.2%	29.5%	24.7%	28.4%
ρ_3	13.8%	12.4%	13.3%	15.6%	20.8%	18.1%	22.8%

in years $t, t+1, \dots, t+4$, for $t = 2000, \dots, 2013$. The shadowed areas surrounding any estimate represent the associated confidence interval. The solid line connects estimates of γ_1 across years relative to covariate distance matrix $\hat{\boldsymbol{D}}_5^1$, whereas the dotted line and the dash-dotted line connect estimates of γ_2 and γ_3 relative to covariate distance matrix $\hat{\boldsymbol{D}}_5^2$ and $\hat{\boldsymbol{D}}_5^3$, respectively.

Lastly, to gain an intuition of the magnitude of decays at varying distances, let ρ_k be the diffusion coefficient at distance k, $k = 2, 3$, constructed as

$$\rho_k \equiv 1 - \left[\frac{\exp(\gamma_1) - \exp(\gamma_k)}{\exp(\gamma_1)}\right], \tag{6}$$

such that the diffusion coefficient measures the residual from the percentage deviation of the odds-ratio of coefficient γ_k from the odds-ratio of γ_1 as estimated in Table 11. Coefficients are reported in Table 11. From the table, we find that on average, information related to transactions diffuses through the network, with 23% and 16% of the information going one and two steps beyond transacting parties, respectively.

6. Conclusions

In this paper we operationalized a novel *FactSet* database on Private Equity (PE) firms transactions to investigate the role of networks in driving secondary buyouts between PE firms. After controlling for economic covariates, we found that PE firms are 2.8 times more likely to transact if they share a common partner, that is both firms belong to the same clique. Importantly, we found that the profitability of such transactions is unambiguously higher relative to the baseline only if these are the result of *repeated* interaction between firms belonging to the same cliques. In other words, a *clique premium* exists under repeated interaction. Lastly, we provided evidence that the economic incentive at the core of clique premium may be related to access to information, and we showed that information related to transactions diffuses through the network, with 23% and 16% of the information going one and two steps beyond transacting parties, respectively.

Clique premium sustains the formation of PE networks. In this work, we analyzed two mechanisms at the core of it, repeated interaction and information diffusion, in relation to an efficiency hypothesis (Jensen, 1989). While we leave an exploration of the "dark side" of PE networks for future research, we encourage regulators to incorporate a network perspective in the analysis of this type of decentralized markets. For example, it would be important to understand the role of clique premia on the increasing popularity of institutional mechanisms meant to crystallize relationships beyond the natural termination of funds (e.g., continuation funds.[48])

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Variable definitions

See Table 12.

[48] See, for example, https://pitchbook.com/news/articles/continuation-funds-secondaries-gp-buyouts.

Table 12
Definition of variables used for ERGM analysis (see Eq. (3)).

Variable label	Definition
Homophily controls x_i	
$Amount\ of\ Funds$	Measure of size of PE firm i (in USD millions).
$Holding\ Period$	Years between acquisition and secondary buyout of transacted firm k by PE firm i.
$Years\ of\ Experience$	Indicates the difference between 2017 and the year in which the PE firm i has been established.
$PE\ Type$	Binary variable constructed using Primary SIC Divisions. It takes value 1 (resp., 0) if corresponding PE firm is *financial engineer* (resp, *operational engineer*). These categories depend on strategy PE firm uses to promote her fund. Financial engineer (resp, operational engineer) is a PE firm raising funds focused on strategies on *leveraged buyouts* (resp. on *early stage* or *seed stage* funds)
$Region$	Categorical variable corresponding to *Africa, Asia, Europe, Latin America, Middle East, North America, Pacific* indicating headquarter location of PE firm.
$Sector$	Categorical variable corresponding to SIC divisions *Construction, Finance, Manufacturing, Mining, Trade, Services, Transportation, Wholesale, Trade*.
Network controls s_i	
$Transaction$	Binary variable taking value 1 if a transaction between PE firms i and j realizes at time t and 0 otherwise.
$GWESP$	*Geometrically weighed edgewise shared partner*. This is a univariate statistics with a parameter α calibrated to $\alpha = 0.2$ to let the statistics coefficient approximate the odds ratio of link formation between two firms sharing at least one PE partner (Goodreau et al., 2008). It is a proxy for the average number of transitive deals (see Section 4.3).

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