Underwriter Networks in Initial Public Offerings

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Current version: December, 2014

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For helpful comments and discussions, we thank Onur Bayar, Raffaele Corrado, Xiaoding Liu, Karthik Krishnan, Xuan Tian, seminar participants at Boston College, Suffolk University, and conference participants at the 2014 Financial Management Association Meetings. We alone are responsible for any errors or omissions.

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Abstract

Using various measures from Social Network Analysis (SNA), we analyze, for the first time in the literature, how various IPO characteristics are affected by the location of the lead IPO underwriter in the network of investment banks generated by its participation in various IPO underwriting syndicates. We hypothesize that investment banking networks perform two possible information-related roles during the IPO process: an information extraction role, where its investment banking network helps the lead underwriter extract credible information useful in pricing the IPO from various institutional investors; or an information dissemination role, where the lead underwriter is able to use its investment banking network to credibly convey its favorable private information about the IPO firm to various institutional investors. Based on these two roles, we develop testable hypotheses relating the location of the IPO underwriter in investment banking networks to the following IPO characteristics: IPO price revision during book-building; IPO and secondary market valuations; IPO initial returns; participation by financial market players such as financial analysts and institutional investors; and long-run post-IPO stock returns. Consistent with our hypotheses, our empirical findings show that more central lead IPO underwriters are associated with larger price revisions; greater IPO and after-market valuations; larger IPO initial returns; greater institutional investor equity holdings and analyst coverage immediately post-IPO; and greater long-run stock returns. Most of these findings are robust to controlling for the endogenous matching between underwriter centrality and IPO firm quality, and are also robust to controlling for various measures of lead underwriter reputation. Overall, our findings are consistent with a strong information dissemination role for investment banking networks in IPOs.

Underwriter Networks in Initial Public Offerings

1. Introduction

Underwriting syndicates are information networks. Starting with Benveniste and Spindt (1989) several theoretical papers have argued that underwriters use the book-building process in IPOs to extract information useful in pricing the IPO from institutional investors. On the other hand, several authors (see, e.g., Chemmanur and Fulghieri (1994)) have argued that the IPO process also serves to credibly disseminate information about the IPO firm's true value from the issuer and underwriter to the investors in the IPO market. In practice, the IPO process may simultaneously accomplish both information extraction from institutional investors to underwriters and information dissemination about the IPO firm from the underwriters to institutional investors, though each role may dominate at different stages in the IPO process. The network of investment banks that a lead IPO underwriter is connected to (through participation in various IPO underwriting syndicates) may play a crucial role in the above information extraction and information dissemination that occurs during the IPO underwriting process.

The objective of this paper is to analyze, for the first time in the literature, how the central position of a lead IPO underwriter within a network of investment banks affects various characteristics of the IPOs underwritten by that underwriter. By making use of information on the interactions between investments banks serving as part of the underwriting syndicates in different IPOs, we are able to use measures from social network analysis (SNA) to characterize the relative position of each investment bank in the network of investment banks that serve as part of these IPO underwriting syndicates. We then empirically analyze how these measures of network centrality of an investment bank serving as a lead IPO underwriter relate to the characteristics of the IPOs underwritten by that investment bank.

We measure the relative position of the lead IPO underwriter in the network of investment banks by making use of six different "centrality" measures which are widely used in the SNA literature. The first measure is *Degree* which is the number of other unique investment banks that the lead IPO underwriter had connections with (either as a lead IPO underwriter or a member of an IPO syndicate) in the five-year period before the IPO year. The second measure is *Outdegree* which is the number of other unique investment banks that the lead IPO underwriter had invited to participate in the IPO syndicates which it led in the previous five-year period. *Outdegree* measures the ability of the lead IPO underwriter to play a leading role in bringing other investment banks together and originating new relationships. The third measure is *Indegree* which is the number of times the lead IPO underwriter was invited to participate in the IPO syndicates led by other underwriting banks in the previous five-year period. *Indegree* measures how desirable the lead IPO underwriter is as a co-manager of IPO syndicates in terms of its contribution of unique expertise and new connections to those syndicates.

The fourth measure we use is *Eigenvector*, which is a measure of the approximate importance of the lead IPO underwriter in the network of investment banks. In essence *Eigenvector* is a recursive measure of *Degree*, where each investment bank in the network is assigned a score based on the idea that connections to more central investment banks contribute more to the score of the investment bank in question than equal connections to low-scoring investment banks. In other words, *Eigenvector* measures the degree to which the lead IPO underwriter is connected to other well-connected investment banks. The fifth measure is *Betweenness* which is the number of shortest paths from all investment banks in the network to all others passing through the lead IPO underwriter. Thus *Betweenness* captures the relative importance of the lead IPO underwriter upon whom other investment banks in the network must rely on as an intermediary to make connections in the network. Finally, our last measure is 2-*StepReach* which is the number of investment banks in the network that can be reached by the lead IPO underwriter by making two steps along the network of investment banks it is connected to. This measure captures the extent to which the lead IPO underwriter can potentially expand its connections (if necessary) by making use of its already established connections to other investment banks. *Eigenvector*, *Betweenness*, and 2-*StepReach* are constructed using the information on established connections in the previous five-year period as well.

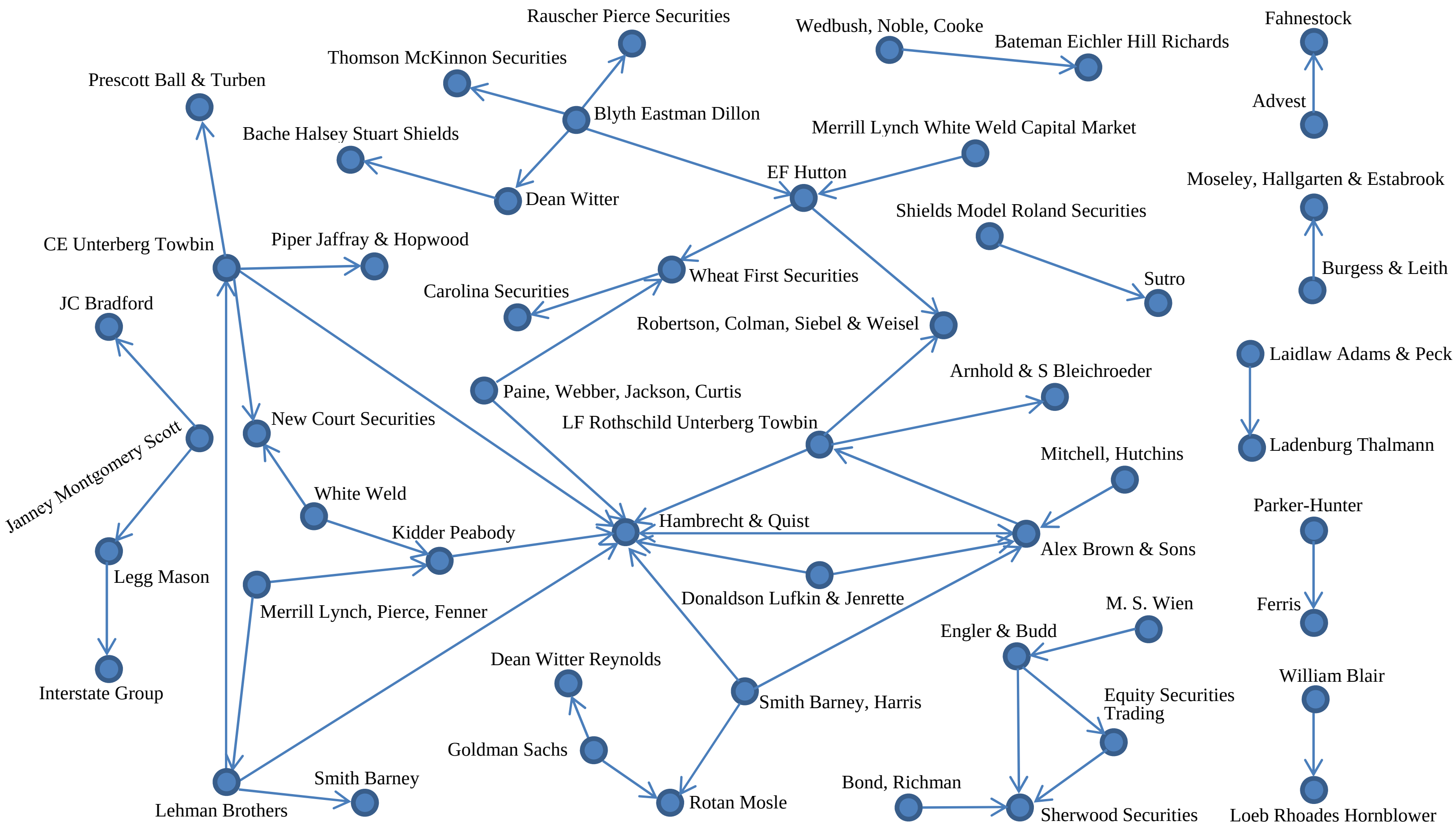

Figure 1. Network of IPO underwriters in 1980.

Arrows between pairs of underwriters indicate that the pair was a part of an IPO syndicate in the previous five-year period (1975-1979). Arrows originate from lead underwriters and point in the direction of non-lead members of IPO syndicates. Two-directional arrows indicate that each underwriter acted both as a lead and a non-lead member of IPO syndicates in the previous five years. Investment banks which underwrote IPOs as sole underwriters and were not a part of any syndicate in the previous five-year period are omitted. We use the network of IPO underwriters in 1980 since it is more manageable for illustrative purposes. The networks of IPO underwriters in later years are much larger and more complex.

In order to illustrate the centrality measures we discussed above, we make use of Figure 1, which shows the network of IPO underwriters using our sample data from 1980. We chose the year 1980 to construct this graph as we had the least amount of connections in that year and thus the graphical presentation of the network of investment banks in 1980 was manageable compared to other years.[1] The arrows represent connections established between investment banks that co-managed IPOs in the previous five-year period. The arrows originate from lead underwriters and point in the direction of non-lead members of IPO syndicates. Two-directional arrows (we have only one between Hambrecht & Quist and Alex Brown & Sons) indicate that each underwriter acted both as a lead and a non-lead member of IPO syndicates in the previous five-year period.

As this graph demonstrates, Hambrecht & Quist had the highest *Degree* centrality in 1980 given that it had the highest number of established connections (8 in total) compared to other investment banks in the network. It also had the highest *Indegree* centrality given that it was invited the most (7 times) as a non-lead member of IPO syndicates. Hambrecht & Quist also had the highest *Eigenvector* centrality since it was connected to other investment banks which, in their turn, also had relatively central positions within the network (such as Alex Brown & Sons and CE Unterberg Towbin). Further, it had the highest 2-*StepReach* centrality in the network as, in addition to its own 8 connections, it could potentially reach another unique 12 underwriters using the connections of the investment banks it was connected to. Hambrecht & Quist also had the highest *Betweenness* centrality given the highest number of shortest paths from all investment banks in the network to all others passing through it. However, Hambrecht & Quist did not have the highest *Outdegree* centrality since it acted as a lead underwriter in IPO syndicates only once (with Alex Brown & Sons as co-manager). CE Unterberg Towbin and Blyth Eastman Dillon had the highest *Outdegree* centrality. Each of these two investment banks acted as a lead underwriter in IPO syndicates 4 times, which is more than any other investment bank in the network. More detailed descriptions of various centrality measures and information on their construction is provided in section 5.

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[1] This graph is for expositional purposes only and is not representative of IPO underwriter networks for the entire sample period of 1980-2009. The networks of IPO underwriters in later years are much larger and more complex.

Precisely how could a more central location of an IPO lead underwriter in investment banking networks affect the characteristics of IPOs underwritten by that lead underwriter? To see this, consider a lead IPO underwriter connected to a number of other investment banks through repeated participation in IPO syndicates, and whose position in these investment banking networks is captured by the SNA measures described above. Let each investment bank in the network be also connected to a number of institutions through repeated interactions. In such a setting, we can think of two ways in which a lead underwriter's position in the network of investment banks may affect the characteristics of IPOs underwritten by it. As briefly mentioned earlier, these two ways are related to the efficacy of information extraction by the lead underwriter and the efficacy of information dissemination.

The theoretical book-building literature that models information extraction by IPO underwriters originated with Benveniste and Spindt (1989). This literature models an IPO underwriter as concerned primarily with extracting truthful information from institutional investors who have private information about their own valuation of the IPO firm. In the above setting, the IPO underwriter uses the book-building and IPO share allocation process to design an incentive compatible mechanism to extract the above information and uses it to more accurately price the shares of the firm going public. In this framework, we introduce a network of investment banks connected (to a greater or lesser degree) to the lead IPO underwriter, with each investment bank having repeated interactions with a subset of institutional investors who may potentially invest in the IPO. Given the repeated interactions between a particular investment bank and certain institutions, that investment bank will be able to efficiently extract information about these institutions' valuation of the IPO firm. Further, a lead underwriter who is better connected to various investment banks will, in turn, be able to more efficiently extract this information from these investment banks and use it in pricing the shares of the firm going public. In summary, the above arguments imply that lead underwriters who are located more centrally in their investment banking networks (as proxied by the various SNA measures discussed above and in more detail in section 5) will be able to extract information useful in pricing IPO firm shares more efficiently from these networks. We will refer to this as the "information extraction hypothesis" from now on.

A second strand in the theoretical literature which models the role of underwriters in IPOs is the literature on certification, a prominent example of which is Chemmanur and Fulghieri (1994). They model a setting in which insiders of a firm going public have private information about their firm's intrinsic value, but where the IPO underwriter can produce information about this value at a cost. Chemmanur and Fulghieri (1994) show that underwriters can credibly convey the (noisy) information they produce about the firm's intrinsic value to potential investors in its IPO using their reputation as a certification mechanism. In this framework, let us introduce a network of investment banks connected (to a greater or lesser degree) to the lead IPO underwriter, with each investment bank having repeated interactions with a subset of institutional investors who may potentially invest in the IPO. Given the repeated interactions between a particular investment bank and certain institutions, that investment bank will be able to credibly (and efficiently) convey its information about the IPO firm's value to these institutions. Further, a lead underwriter who is better connected to various investment banks will be able to convey the information it has produced about the true value of the IPO firm to these investment banks, which, in turn, will be able to credibly pass it on to the subset of institutions they interact with repeatedly. We will refer to this hypothesis as the "information dissemination hypothesis" from now on.

As we discuss in detail in section 3 (where we discuss the underlying theory and develop testable hypotheses), it can be shown that, depending on whether the information dissemination or the information extraction role of investment banking networks dominates, more centrally located lead underwriters will be associated with higher or lower levels of IPO price revisions during book-building. Further, a more central position for the lead underwriter in investment banking networks will be associated with a higher IPO and immediate after-market valuation of the IPO firm's equity as well as IPO initial returns; greater participation by important financial market players such as institutional investors and financial analysts (the former by holding equity in the IPO firm and the latter by providing analyst coverage); and (under certain additional assumptions discussed in section 3) better long-run post-IPO stock returns.

Our empirical results can be summarized as follows. First, we find that, consistent with the testable hypotheses developed in section 3, IPOs underwritten by lead underwriters who are positioned more centrally in their respective investment banking networks are associated with larger IPO offer price revisions. This indicates that, overall, the information dissemination role of investment banking networks dominates the information extraction role, at least in this early stage in the IPO process. Second, IPOs underwritten by lead underwriters who are positioned more centrally in their investment banking networks are also associated with greater IPO and secondary market valuations, and greater initial IPO returns. Third, IPO firms which are underwritten by more central lead underwriters generate a greater interest on the part of financial market players, e.g., such firms are followed by a greater number of financial analysts and have larger institutional investor holdings. Finally, IPO firms underwritten by more central lead underwriters realize better post-IPO long-run (six-months and one-year) stock returns. It is important to note that all the above results hold even after controlling for various measures of underwriter reputation. In general, our results are consistent with the notion that lead IPO underwriters which are centrally located within networks of investment banks are able to disseminate their favorable private information about the firm they are taking public more credibly and efficiently to the investment banks in the network, and through them, to the institutional investors that each investment bank may repeatedly interact with (in the IPO as well as non-IPO related service contexts).

It may be argued that underwriter centrality is potentially endogenous, since more central underwriters may be more likely to take higher quality firms public. In order to control for this potential endogeneity and to establish a causal relationship between underwriter centrality and IPO characteristics, we conduct an instrumental variable analysis of the effect of underwriter centrality on various IPO variables we study in this paper. An appropriate instrument should create an exogenous variation in the various centrality measures that characterize each underwriter. We use the repeal of the Glass-Steagall Act in 1999 as an instrument for underwriter centrality, since commercial banks could serve as IPO underwriters after the repeal and therefore there is likely to be an exogenous change (increase) in various measures of underwriter centrality after the repeal (unrelated to IPO firm quality). We use a categorical variable which takes a value of two for the firms which went public in 2005-2009, one for the firms which went public in 2000-2004, and zero for the firms which went public in 1980-1999 as our instrument for underwriter centrality. We make sure that this categorical variable is a valid instrument by first verifying that there is a significant increase in the various SNA measures from before the passage of the act to after. Since there is no reason to believe that the quality (intrinsic value) of firms going public is likely to have increased from before the passage of the act to after, the exclusion restrictions for this instrument are likely to be satisfied. The findings of our instrumental variable analyses are similar (with two exceptions) to those of our OLS regression analyses discussed earlier, indicating that our results on the relationship between underwriter centrality and various IPO variables are robust to controlling for the potential endogenous matching between more central underwriters and higher quality firms.[2]

The contribution made by this paper is two-fold. First, this is the first paper to study the effectiveness of underwriters in extracting and disseminating information about the firms they take public by making use of the network of investment banks that they are connected to. We analyze this effectiveness by studying the relationship between various SNA measures characterizing the location of a lead IPO underwriter in investment banking networks and the IPO characteristics (as well as the post-IPO stock return performance) of firms they take public. Second, underwriter reputation has been seen in the existing literature as the most important measure capturing the effectiveness of investment banks in taking firms public. We contribute to the IPO literature by showing that various SNA measures may serve as important additional variables to help us to assess the above effectiveness.

The rest of this paper is organized as follows. Section 2 discusses how our paper is related to the existing literature. Section 3 discusses the underlying theory and develops testable hypotheses. Section 4 describes our data and sample selection procedure. Section 5 describes our measures of lead IPO underwriter position in investment banking networks and discusses how we compute these measures. Section 6 describes our empirical tests and results. Section 7 concludes.

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[2] The two exceptions are IPO initial returns and long-run post-IPO stock returns, where we do not find significant relationships between lead IPO underwriter centrality measures and these IPO variables (unlike in our OLS analysis). However, this lack of relationship based on our instrumental variable analysis is not very surprising, since, as we explain in footnotes 13 and 14, respectively, we expect the underlying economic relationship to be weakest in the case of these two IPO variables.

2. Relation to the Existing Literature

Our paper is related to several strands in the literature. The first and most closely related is the theoretical and empirical literature on IPOs in general and in particular on the economic role of underwriters in IPOs. A number of papers have modeled various aspects of the roles played by investment banks and institutional investors in IPOs: see, e.g., Benveniste and Spindt (1989), who model the information extraction role of investment banks, and Chemmanur and Fulghieri (1994), who model the information dissemination role.[3] There is also a large empirical literature studying the information flows in IPOs: one example is the literature on the partial adjustment phenomenon (e.g., Hanley (1993)) and the more recent literature on the efficiency of the IPO process in general (e.g., Lowry and Schwert (2004)). There is also a recent paper by Cooney, Madureira, Singh, and Yang (2012) who study whether social ties (through executives or directors) between an IPO firm and the investment bank serving as a book manager of its IPO increase the likelihood of that investment bank being included in the IPO syndicate. Unlike our paper, they do not study the effect of lead IPO underwriter centrality on IPO characteristics. The empirical literature on the role played by underwriters in the IPO process (see, e.g., Michaely and Womack (1999) and Ellis, Michaely, and O'Hara (2000)) and that played by institutional investors in IPOs (see, e.g., Aggarwal (2003) and Chemmanur, Hu, and Huang (2010)) is also distantly related.[4]

The second literature that our paper is related to is the emerging literature on social networks in a financial market or in a financial intermediary setting. For example, Hochberg, Ljungqvist, and Lu (2007) study how networks of venture capitalists (VC) affect the investment performance of VC funds. They show that VC funds whose parent firms enjoy more influential network positions realize significantly better performance (measured by the proportion of portfolio investments successfully exited through an

[3] There are also several information driven models of IPO underpricing, which are indirectly related to this paper: see, e.g., Chemmanur (1993), Allen and Faulhaber (1989), Welch (1989), or Welch (1992). Further, to the extent that our study is related to information flows around a firm's IPO, it is also indirectly related to models of going public versus remaining private decision by the desire of firm insiders to avoid revealing private information (e.g., Bhattacharya and Ritter (1983)) or by considerations of minimizing duplication in information production by outsiders (e.g., Chemmanur and Fulghieri (1999)).

[4] The empirical literature on the long-run performance of IPO firm equity is also related: see, e.g., Ritter (1991), Loughran and Ritter (1995). See also Ritter and Welch (2002) for a review of the theoretical and empirical literature on IPOs.

IPO or a sale to another company). Engelberg, Gao, and Parsons (2012) show that, when banks and firms are connected through interpersonal linkages, interest rates are markedly reduced. There is also a large literature on board and CEO connectedness: for example, Larcker, So, and Wang (2013) investigate the "connectedness" of corporate board members across firms, and show that firms with the best-connected boards earn on average substantially higher future excess returns compared to firms with the worst-connected boards. In a similar vein, El-Khatib, Fogel, and Jandik (2012) study the effects of CEO connectedness on merger performance. Despite this large literature on how networks of financial intermediaries and corporate officers affect firm performance, there has been no literature analyzing how investment banking networks affect IPO characteristics, which is our objective in this paper.[5]

3. Theory and Hypotheses Development

There are two strands in the theoretical literature regarding the role of underwriters in IPOs. The first strand is the theoretical book-building literature originated by Benveniste and Spindt (1989). This literature models an IPO underwriter as concerned primarily with extracting truthful information from institutional investors who have private information about their own valuation of the IPO firm. In the above setting, the IPO underwriter uses IPO share allocation process to design an incentive compatible mechanism to extract the above information and uses it to more accurately price the IPO firm's shares. In this framework, we introduce a network of investment banks connected (to a greater or lesser degree) to the lead IPO underwriter, with each investment bank having repeated interactions with a subset of institutional investors who may potentially invest in the IPO. Given the repeated interactions between a particular investment bank and certain institutions, that investment bank will be able to efficiently extract information about these institutions' valuation of the IPO firm.[6] Further, a lead underwriter who is better connected to various investment banks will, in turn, be able to more efficiently extract this information

[5] An exception is the unpublished Ph. D. dissertation by Chuluun (2009), who, however, focuses on how the network position of an investment bank affects its subsequent market share in the market for IPO underwriting and for merger advisory services.

[6] In the dynamic extension to their model, Benveniste and Spindt (1989) show that extraction of truthful information from institutional investors is easier when an investment bank interacts repeatedly with these institutional investors.

from these investment banks and use it in pricing the IPO firm's shares. Thus, this implies that lead underwriters who are more centrally located in investment banking networks (as proxied by the various SNA measures discussed in section 5) will be able to extract information useful in pricing IPO firm shares more efficiently from these networks. We will refer to this as the "information extraction hypothesis."

The second strand is the theoretical literature on underwriter certification, a prominent example of which is Chemmanur and Fulghieri (1994). They model a setting in which insiders of an IPO firm have private information about their firm's intrinsic value, but where the IPO underwriter can produce information about this value at a cost. Chemmanur and Fulghieri (1994) show that underwriters can credibly convey the noisy information they produce about the intrinsic value of the firm they take public to potential investors in its IPO using their reputation as a certification mechanism. In this framework, we introduce a network of investment banks connected (to a greater or lesser degree) to the lead IPO underwriter, with each investment bank having repeated interactions with a subset of institutional investors who may potentially invest in the IPO. Given the repeated interactions between a particular investment bank and certain institutions, that investment bank will be able to more credibly (and efficiently) covey its information about the IPO firm's value to these institutions.[7] Further, a lead underwriter who is better connected to various investment banks will be able to convey the information it has produced about the true value of the IPO firm to these investment banks more efficiently. These investment banks, in turn, will be able to credibly pass it on to the subset of institutions they interact with repeatedly. We will refer to this hypothesis as the "information dissemination hypothesis."[8]

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[7] This follows from the fact that the reputation of an investment bank as assessed by institutions with which it has repeated interactions will be greater, giving it more credibility in conveying information to these institutions (using the arguments made by Chemmanur and Fulghieri (1994)).

[8] Note that, while we use the theoretical IPO models of Chemmanur and Fulghieri (1994) and Benveniste and Spindt (1989) to develop our information dissemination and information extraction hypotheses, respectively, regarding the effects of the interactions between IPO underwriters and institutional investors on various IPO characteristics, both of these models involve a single underwriter and multiple investors. Therefore, neither of the above two papers explicitly model how information is transmitted from one investment bank to another in an underwriting network of investment banks. The process of information transmission across the investment banks in a network about the true value of an IPO firm that we rely on here (which is consistent with both information extraction as well as information dissemination) is modeled by the seminal network interaction model of information transmission by DeGroot (1974), which suggests that, in general, the structure of a network influences the spread of information among the agents in that network. More recently, rational information transmission across agents in a network has

We would like to emphasize that the two roles of IPO underwriting networks discussed above are not mutually exclusive, though, in some contexts, one or the other role may dominate. Indeed, the practitioner literature on IPOs points to the two-way information flow occurring during IPO road-shows and the book-building process between IPO underwriters and institutions: while, on the one hand, underwriters collect information about the demand schedule of institutional investors for the IPO firm's shares, they also address institutional investors' questions and concerns about the future strategy and performance of the firm going public, thus disseminating information about the firm to them.

In the rest of this section, we will discuss the implications of the above two roles of underwriter networks for the relationship between lead IPO underwriter centrality and various IPO characteristics.

3.1. Underwriter Networks and IPO Offer Price Revision

A more central location of lead IPO underwriters in their respective networks will allow them to perform two functions, as discussed earlier. The first function is information extraction. More central underwriters may be in a better position to extract information useful for valuing the shares of the IPO firm from the members of their network. If this is the case, then one would expect a *negative* relationship between underwriter centrality and *absolute* offer price revisions, since more central underwriters would set their initial pricing range (and its mid-point) closer to the eventual IPO offer price (**H1A**).[9]

The second function is information dissemination. More central underwriters may be in a better position to disseminate information about the IPO firm within as well as outside of their network. If this is the case, then one would expect a *positive* relationship between underwriter centrality and offer price revisions (**H1B**). This is because more central underwriters will be in a better position to credibly convey

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also been modeled by DeMarzo, Vayanos, and Zwiebel (2003). See Jackson (2008) for an excellent discussion of theoretical models of information transmission in social and economic networks.

[9] The process of valuing IPO firm shares starts with establishing the filing range immediately prior to filing the preliminary prospectus with the SEC, continues with the book-building process, and culminates in establishing the IPO offer price (typically the night before the first trading day). Under the information extraction hypothesis, we expect more central underwriters to extract information earlier and more efficiently, so that the price revision from the mid-point of the filing range to the IPO offer price is smaller for the IPOs underwritten by such underwriters.

favorable information about the true value of the IPO firm to the other investment banks in their network and through them to various institutional investors, thereby increasing their valuation of the IPO firm.

3.2. Underwriter Networks, IPO and Secondary Market Valuations, and IPO Initial Returns

Under the information dissemination hypothesis, more centrally located lead underwriters will be associated with higher IPO valuations (measured, for example, by the Q ratio at the IPO offer price) (**H2**). This is because more central underwriters will be able to credibly disseminate favorable information about the value of the firm they are taking public to investment banks in their network and, through them, to various institutions. This, in turn, implies a larger institutional demand, *ceteris paribus,* for the shares of firms taken public by more central underwriters, resulting in higher IPO market valuations.[10]

More centrally located lead underwriters will also be associated with higher (immediate) secondary market valuations for the IPO firm (**H3**). This is because such underwriters will be able to credibly convey favorable information about the value of the firm they are taking public to institutional investors in the secondary market (those who participated in the IPO as well as those who did not participate in the IPO and who may be potential buyers of the firm's equity in the secondary market).[11, 12]

[10] The ability of the lead IPO underwriter to efficiently extract information from investment banks in its network may also matter for IPO valuation. While there is no consensus in the theoretical and empirical literature on precisely how the IPO offer price is set, this price-setting process can be broadly thought of as the following. During the book-building process, the lead underwriter extracts information about the valuation of the IPO firm by institutional investors. Simultaneously, the lead underwriter (as well as the top corporate officers of the firm) may attempt to credibly convey favorable information about the firm to these institutional investors (this, in turn, may affect their valuation of the firm). Toward the end of the IPO marketing process (book-building and road-show), once the lead underwriter establishes the highest uniform price at which they can sell all shares offered in the IPO (i.e., the market clearing price), the underwriter may apply a "discount" to this highest possible offering price, thus establishing the actual IPO offer price (typically on the evening before the IPO). There is no consensus in the theoretical IPO literature on the reason underlying the discount. Various papers have argued that this may be for signaling purposes (Allen and Faulhaber (1989), Welch (1989)), or for inducing information production by outsiders (Chemmanur (1993)), or for reducing litigation risk (Tinic (1988), Hughes and Thakor (1992)). Regardless of the reason underlying the IPO discount, the above mentioned IPO offer price-setting process implies that the ability of more centrally located underwriters to efficiently extract information from institutional investors about their valuation of the IPO firm may also lead to higher IPO valuations for firms whose IPOs are underwritten by such underwriters.

[11] It is reasonable to assume that institutional investors who participated in the IPO are less likely to "flip out" of these shares if they possess more favorable information about the firm (and may even buy additional shares in the secondary market). This means that IPO firm's secondary market valuation will be higher if the lead underwriter is able to credibly disseminate more favorable information about the IPO firm to institutional investors in the secondary market.

The effect of lead underwriter centrality on IPO initial returns (underpricing) is *ex ante* ambiguous. If the information dissemination effect of lead underwriter centrality is stronger on IPO valuation than on secondary market valuation, then the relation between lead underwriter centrality and IPO initial returns will be negative (**H4A**), since the IPO initial return simply measures the return from the IPO offer price to the first day secondary market closing price. On the other hand, if the effect of lead underwriter centrally is stronger on short-term secondary market valuation than on IPO valuation, then the relation between lead underwriter centrality and IPO initial returns will be positive (**H4B**).[13]

3.3. Underwriter Networks and the Participation of Financial Market Players in the IPO

As discussed earlier, lead underwriters who are more centrally located in their networks may be able to disseminate favorable information about the IPO firm more credibly to institutional investors. This implies that the participation by institutional investors will be greater for IPOs underwritten by more centrally located lead underwriters. Further, given the reduction in the cost of producing information about an IPO firm incurred by analysts following more efficient information dissemination, the analyst coverage of such IPO firms will also be greater (**H5**).

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[12] Here the underlying assumption is that all the information relevant for valuing the firm does not get exogenously released into the immediate secondary market, so that the underwriter plays a crucial role in conveying this information to secondary market investors. This assumption seems to reflect the situation in real-world secondary markets (at least in the short-run). For example, during the internet bubble period (1999-2000) most internet firms were highly overvalued not only in the IPO but also in the immediate after-market.

[13] To see the intuition behind hypotheses **H4A** and **H4B**, it is useful to consider the two extreme cases. First, consider the case where the relation between the centrality of a lead underwriter and IPO valuation is as postulated in hypothesis **H2**, but there is no relation between the centrality of the lead underwriter and secondary market valuation. In this case, since the relation between the centrality of lead underwriter and IPO market valuation dominates, the relation between the former and IPO initial returns will be negative (since the initial return will be smaller for IPOs underwritten by more central lead underwriters). Conversely, if the relation between the centrality of the lead underwriter and immediate post-IPO secondary market valuation is as postulated in hypothesis **H3**, but there is no relation between the centrality of the lead underwriter and IPO valuation, then the relation between the centrality of the lead underwriter and IPO initial return will be positive (since the initial return will now be larger for IPOs underwritten by more central lead underwriters).

3.4. Underwriter Networks and the Long-Run Stock Return Performance of IPO Firms

Even though, as we discussed above, more centrally located underwriters may be better at disseminating information to institutions and other investors in the IPO as well as in the secondary market, not all value-relevant information may be fully reflected in the secondary market prices immediately. In other words, some of this information may get reflected in the secondary market price of the IPO firm only gradually over time. If this is the case, then we would expect IPOs underwritten by more centrally located lead underwriters to have better long-run post-IPO stock returns (**H6**).[14]

4. Data and Sample Selection

The list of U.S. IPOs in 1980-2009 comes from the SDC/Platinum Global New Issues database. Following the IPO literature, we exclude real estate investment trusts (REIT), closed-end funds, unit IPOs and unit investment trusts, rights issues, spin-offs, equity carve-outs, financial firms (with SIC codes between 6000 and 6999), foreign firms, leveraged buy-out firms (LBO) and former LBOs, tracking stocks, and duplicate observations. Thus our final sample consists of 6,217 IPO firms. Information on IPO underwriters and underwriting syndicates, as well as various IPO characteristics were taken from the SDC/Platinum Global New Issues database. Information on institutional shareholdings was obtained from Thomson Reuters institutional (13F) holdings database. Accounting data came from Compustat and stock price data came from CRSP. Firm age data came from Jay Ritter's website and was supplemented from various other sources.

[14] If all the information disseminated by the lead underwriter through its investment banking network is reflected in the IPO firm's immediate secondary market valuation, we would not expect any relationship between underwriter centrality and long-run stock returns. However, there may be a variety of reasons why the immediate after-market stock price may not efficiently reflect all the information disseminated by the lead underwriter about the IPO firm: e.g., bounded rationality of retail investors in the immediate IPO after-market. Note that all long-run stock return studies around corporate events require the assumption of bounded rationality or limited market efficiency, similar to the one we make here. One may consider this to be a strong assumption, but, given the large empirical literature documenting post-event drift following earnings announcements and many other corporate events (see, e.g., Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989)), one has to at least consider the possibility that the information revealed by many corporate actions taken by a firm is not always instantaneously reflected in its stock price.

5. Measures Characterizing Underwriter Networks

In order to measure how central the lead IPO underwriter is within its network of investment banks, we employ measures from the SNA literature. It has been argued in the SNA literature that the central location of an agent in a network and the nature and extent of its connections to other agents in that network affect the flow of information to and from that agent. The seminal theoretical study of Lazarsfeld, Berelson, and Gaudet (1944) argues that social networks play an important role in information transmission among individuals; Katz and Lazarsfeld (1955) develop this theory further, and show empirically the importance of opinion leaders (who convey their information to other individuals who are less directly informed) in affecting the voting and household purchase decisions of various individuals. Another influential study (set in the labor market) is Granovetter (1995), who shows the importance of the social ties among individuals in determining how applicants learn about various job opportunities.

In a similar manner, we hypothesize that the nature and extent of the connections of an IPO underwriter to other investment banks in its network affect its ability to extract or to disseminate information about the IPO firm. We consider two investment banks as having a "connection" or "tie" if they have been part of the same IPO syndicate in the past. We characterize the location (or "centrality") of an investment bank in the network of investment banks generated by its connections using various measures from the SNA literature that we will describe below: we will refer to these measures as "centrality measures" from now on. Given the nature of the IPO underwriting business, the change in the composition and size of IPO syndicates, and the increasing concentration of the underwriting industry, we compute our centrality measures using 5-year trailing periods (similar to Hochberg, Ljungqvist, and Lu (2007) in the context of venture capital syndicates). Thus, in order to analyze the effect of lead underwriter centrality on an IPO conducted in a given year, we consider the IPO underwriting syndicates in which that lead underwriter has participated during the previous five years.

There are several centrality concepts that have been put forward in the SNA literature, each one capturing different aspects of social and economic networks. We make use of six different measures of centrality which are commonly used in the SNA literature. Four of them (*Degree*, *Indegree*, *Outdegree*, and *Eigenvector*) essentially measure the number of ties of an underwriter with other investment banks. The underlying idea is that the higher the number of connections an underwriter has, the more centrally located it is within the network. The fifth measure (2-*StepReach*) counts the number of connections that are two steps away from a lead underwriter. This metric is similar to the first four measures of centrality (counting the number of connections) but under the assumption that indirect ties also matter. Finally, the last measure, *Betweenness,* assesses to what extent an investment bank is able to act as a bridge between two groups of other investment banks which are not otherwise linked. We will discuss the construction of each of these measures in more detail below.

In order to compute the above centrality measures we first need to construct an adjacency matrix *X*, which is an *N* by *N* matrix (with *N* being the number of investment banks in the network) where each cell takes a value of one if two underwriters have co-underwritten the same IPO over the five-year period considered ($x_{i,j}$ = 1 if investment bank *i* has co-underwritten an IPO with investment bank *j*). In the case of "undirected networks" we ignore the information regarding which bank was the one inviting other banks into an IPO syndicate, and as a result the adjacency matrix is necessarily symmetric. Thus, if banks *i* and *j* have participated in underwriting the same IPO and we do not consider which one is the lead underwriter, it follows that $x_{i,j} = x_{j,i} = 1$. However, with "directed networks" it also matters whether bank *i* has invited bank *j* into an IPO syndicate or vice versa. In this case, each cell in the adjacency matrix takes a value of one only if bank *i* has invited bank *j* to take part in an underwriting syndicate (thus, $x_{i,j} = 1$ and $x_{j,i} = 0$). By taking into consideration the direction of the connection, we can embed into some centrality measures the type of relationship that has been established between the two. As we discuss in more detail when we describe the construction of various centrality measures below, *Degree*, *Eigenvector*, 2-*StepReach*, and *Betweenness* use only undirected networks, while *Indegree* and *Outdegree* make use of directed networks.

5.1. Degree Centrality

Among the centrality measures mentioned above, *Degree* is certainly the most intuitive and straightforward. *Degree* is simply the number of total connections (nodes) that a specific agent has in the network. Formally, given the adjacency matrix *X*, the *Degree* (d_i) for agent *i* is

$$d_i = \sum_j x_{ij} \ , \qquad (1)$$

which is the sum of the row (or column) of the adjacency matrix. As we mentioned before, the networks that we consider are comprised of investment banks acting as IPO underwriters (agents) which are tied to each other by having co-participated in an IPO syndicate at least once over the last five-year period. Accordingly, *Degree* measures the total number of IPO syndicate partners of a given investment bank. Despite its frequent use and the fact that it is considered the most important measure of network centrality, in a strict sense *Degree* does not provide complete information concerning the (central) position of an agent in a network, as it can be computed without having full information about the entire structure of the network.[15] However, it does provide useful information for our purpose, as it proxies for the capacity of an investment bank to either extract or to disseminate information, since the higher the number of ties, the easier the information flow.[16]

A clear shortcoming of *Degree* is that it is a function of the size of the network. Given the "centrality" of a particular agent, bigger networks produce a larger *Degree* as there are more connections in place. This may not necessarily be a problem in cross-sectional analysis; however it might introduce a time-bias. In fact, over the sample period (1980-2009) IPO underwriter networks have changed both in size (became larger) and in composition (they became more concentrated). In order to control for this potential bias, we normalize *Degree* by dividing it by the maximum possible number of connections, which is $N - 1$. Accordingly, the normalized *Degree* ($\hat{d}_i$) for underwriter *i* is:

$$\hat{d}_i = \frac{1}{N-1} \sum_j x_{ij} = \frac{d_i}{N-1} \ . \qquad (2)$$

From now on we refer to *Degree* in the sense of normalized *Degree*.

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[15] In fact, *Degree* only uses a vector of the adjacency matrix. Moreover, if a player has *n* connections to other players that have no other ties, its *Degree* (equal to *n*) will be the same as in the case where the other players are well connected themselves. Thus, in the first case the considered agent plays a more central role in the network then in the second case, despite the same *Degree*.

[16] It can be shown that if a stochastic variable (i.e. information) follows a random walk through the network, the probability of reaching a specific node is proportional to its *Degree.*

5.2. Indegree and Outdegree

As it has been pointed out, undirected networks do not differentiate between who invites whom into an IPO syndicate. As a result, the adjacency matrix is symmetric and it is impossible to establish which investment bank is a leader in a syndicate and which one is a follower. Accordingly, *Degree* does not capture whether an investment bank has a leading position in the syndicate or has the position of a desirable partner.

A possible solution to this problem is using directed networks, where the direction of the relationship is also taken into consideration. This produces measures such as *Indegree* and *Outdegree*, which only consider the number of passive or active connections (respectively), and allows us to distinguish between the two cases. *Indegree* counts the number of ingoing connections where the underwriter is invited to act as a co-manager in an IPO syndicate. *Outdegree*, on the other hand, counts the number of outgoing connections where the underwriter, acting as a lead manager, selects and invites other members of the syndicate. An underwriter with a high level of *Outdegree* originates relationships and decides which other partners are more suitable to be a part of the syndicate. In that sense, a more central (high *Outdegree*) underwriter can select other banks based on the type of information needed to be extracted or disseminated. Conversely, an underwriter with a high level of *Indegree* is desirable as a co-manager and has access to valuable information (due to the number of underwriting co-partners) but may not necessarily have the capacity to propagate information (given the subordinate role).

Indegree and *Outdegree* are computed as in equation (2) after making certain changes in the adjacency matrix. Specifically, since we aim to isolate only a certain direction of the relationship, each cell of the matrix takes a value of one only if the ingoing (outgoing) tie has been detected. For instance, if the investment bank i is the lead underwriter who is inviting the investment bank j to take part in an IPO syndicate, we set $x_{ij} = 1$ and $x_{ji} = 0$ in measuring *Outdegree*, and we do the opposite (set $x_{ij} = 0$ and $x_{ji} = 1$) in measuring *Indegree*. Unlike undirected networks (where the adjacency matrix is by construction symmetric), in directed networks the rows and the columns of the matrix are different. If rows (columns) capture the outgoing (ingoing) relationships, the sum of the row produces *Outdegree* whereas the sum of the column produces *Indegree*. As in the case of *Degree*, we normalize *Indegree* and *Outdegree* by dividing by the number of maximum connections, $N - 1$.

5.3. Eigenvector

One of the limitations of the measures described above is that the simple count of connections does not necessarily capture the prominence of a particular agent within the network. Specifically, if an agent has high *Degree* centrality but most of his connections are to other agents who themselves are not well connected, then the power exercised by this agent over the entire structure of the network is somewhat limited. On the other hand, if the agent is tied to other agents who themselves are well connected (more central), she will have a greater influence in the network. This concept is captured by *Eigenvector* centrality, which is a variation of *Degree* centrality where connections are weighted by their relative importance in the network. In other words, *Eigenvector* does not simply count the number of ties that the agent has, but it weighs each connection by its centrality. Therefore, being connected to more central players generates a higher *Eigenvector* score than being connected to more peripheral players.[17] In our context, *Eigenvector* is a better measure of an underwriter's ability to manage information. A higher *Eigenvector* measure indicates that an underwriter may be able to extract and disseminate information more efficiently as the information flows through other investment banks who themselves are more central and informed.

Formally *Eigenvector* (e_i) for underwriter *i* is calculated as:

$$e_i = \lambda \sum_{j=1}^{N} x_{ij} e_j \ , \qquad (3)$$

where λ is a constant represented by the biggest eigenvalue of the adjacency matrix and e is the eigenvector centrality score. Equation (3) is essentially a modified version of equation (1); it is not simply

[17] This measure is similar to the algorithm used by Google to rank the importance of web sites (PageRank). The algorithm takes into consideration both the quantity and the quality of links to other web pages, where the quality is determined by the importance of the websites from which the website receives links.

an algebraic sum but a weighted sum of all the connections in place. Further, we normalize *Eigenvector* by dividing it by the maximum possible eigenvector element value for an *N* agent network.

5.4. 2-*StepReach*

2-*StepReach* centrality is a particular form of *k*-*StepReach* centrality which is the number of distinct agents within *k* ties of a given agent. Thus, this centrality measure counts the number of agents that can be reached directly (1-step) or indirectly via other agents that are 1-step away. In other words, 2-*StepReach* considers not only direct but also indirect connections.

By adding an additional layer of connections, 2-*StepReach* provides us with a simple and more complete measure of the ability of an underwriter to receive or send information within its network. For instance, if an underwriter has only one connection, but the agent it is connected to is a very prominent and informed player, no version of *Degree* will tell us about its (relatively high) central position in the network. *Eigenvector* will be a better measure than *Degree*, since it tells us that the only connection in place has a higher weight. However, neither *Degree* nor *Eigenvector* measure indirect connections, which is accomplished by 2-*StepReach*.

Assuming that information flows not only through direct connections (partnerships in the same deal) but also indirectly through interposed relationships, 2-*StepReach* provides us with a better measure of underwriter centrality. This may be particularly true in the IPO underwriting business. For instance, if an investment bank is connected to only one prominent investment bank, which, in its turn, has many connections to other investment banks, it is quite likely that the former will be able to benefit from these indirect connections in terms of extracting or disseminating information throughout the network.

5.5. Betweenness

The five measures of centrality described earlier are somewhat similar since they are constructed using the number of connections that an agent has with other agents in the network. In contrast, *Betweenness* is constructed using a different idea of centrality that is represented by the ability of an agent to serve as a link between two (or more) disconnected (or not directly connected) groups of other agents. *Betweenness* of an agent in the network is measured by making use of the concept of geodesic paths, which are the shortest chains or ties through which two agents are connected in a given network, and estimating the number of (shortest) paths passing through that agent. In other words, given the total number of possible paths between two other agents, the higher the number of cases where the shortest path passes through the given agent, the higher will be the *Betweenness* of that agent. Formally *Betweenness* (b_i) for agent i is

$$b_i = \sum_{j<k} \frac{p_{ijk}}{p_{jk}}, \qquad (4)$$

where p_{ijk} is the number of geodesic paths between agents j and k passing through agent i and p_{jk} is the total number of geodesic paths between agents j and k. In other words, *Betweenness* measures how frequently a given agent represents the shortest path between two other agents. If an agent is isolated in the network or every other agent it is connected to is well-connected itself, its *Betweenness* will be zero. If an agent stands on every shortest path between any pair of other agents, that agent's *Betweenness* will be at the maximum. Intuitively, the highest *Betweenness* is achieved where two sub-networks are linked only through a single agent who acts as a bridge between them. In this case every agent of one sub-group is connected to every other agent in the other sub-group through only one possible link.

In the network literature *Betweenness* is often interpreted as a measure of controlling flows within the network. An agent with high *Betweenness* will be able to act as a gatekeeper and consequently manage and mediate the relationships among other agents. In our setting, a more central (high *Betweenness*) underwriter will be in a position to act as a broker with respect to other underwriters. This privileged position is likely to allow the underwriter to more easily extract or disseminate information as well as to control the type of information conveyed. In fact, information in disconnected networks will be available to the agents of the same sub-network and to the gatekeeper, but not to all other agents. As a result, on the one hand, the more central (high *Betweenness*) underwriter will be the only one having access to information coming from each disconnected sub-network; on the other hand, if any information between sub-networks has to go through the more central (high *Betweenness*) underwriter, it will be able to filter and mediate the content. For instance, the more central (high *Betweenness*) underwriter may omit undesired elements or change the tone of the information to produce the desired sentiment.

6. Empirical Tests and Results

In this section we present our methodology and empirical findings. Table 1 reports the summary statistics of both independent (lead IPO underwriter centrality measures and other controls) and dependent (various IPO characteristics) variables used in our regression analyses in subsequent sections. Table 1 shows that, on average, lead IPO underwriters in our sample were connected to 10.6% of investment banks in investment banking networks constructed for a given year (as described in the previous section) serving either as lead IPO underwriters or IPO underwriting syndicate members (*Degree*); connected to 3.2% of investment banks in investment banking networks serving as IPO underwriting syndicate members (*Indegree*); and connected to 9.4% of investment banks in investment banking networks serving as lead IPO underwriters (*Outdegree*). Table 1 also shows that, on average, lead IPO underwriters in our sample had eigenvector centrality equal to 10.2% (*Eigenvector*); could reach 43.8% investment banks in investment banking networks using their indirect (two steps away) connections (2-*StepReach*); and 2.6% of the shortest paths between two investment banks in investment banking networks passed through the lead IPO underwriters in our sample (*Betweenness*).

6.1. Underwriter Centrality and IPO Offer Price Revision

We study the relationship between underwriter centrality and IPO offer price revision by running a series of regressions with two dependent variables: *Revision*, defined as the percentage difference between the IPO offer price and the midpoint of original filing range, and *AbsRevision*, which is the absolute value of *Revision*. We use *AbsRevision* as the dependent variable in our regressions to test the information extraction hypothesis **H1A** and we use *Revision* as the dependent variable to test the information dissemination hypothesis **H1B**.

Independent variables in our regressions are the six lead IPO underwriter centrality measures and other controls. We control for underwriter reputation defined as the lead underwriter's share of total proceeds raised in the IPO market in the previous five years (*MktShare*). Similar to underwriter centrality, more reputable underwriters on the one hand may be in a better position to value IPO firms correctly and therefore less likely to revise IPO offer price; on the other hand, more reputable underwriters may generate more information during the waiting period which in its turn will make offer price revisions more likely.[18] *MktShare* has a relatively high correlation with underwriter centrality measures creating multicollinearity problems in our regressions, and therefore we use the residuals from a regression of *MktShare* on six lead IPO underwriter centrality measures (*xMktShare*) as a control variable in our regressions. Further, offer price revisions are more likely if there is more uncertainty about IPO firm's value (see, e.g., Benveniste and Spindt (1989)). To control for such uncertainty we use several controls. First, we control for firm size and firm age by including the natural logarithm of the book value of assets at the end of the fiscal year prior to the IPO (*LnAssets*) and the natural logarithm of one plus the number of years from IPO firm founding year to the IPO year (*LnAge*). Larger and older firms are expected to have less uncertainty about their value. We also control for IPO offer size by including the natural logarithm of IPO total proceeds (*LnOffer*). Larger firms are expected to have larger offer sizes and therefore firms making larger offers are expected to have less uncertainty. Similar to *MktShare*, this variable has a relatively high correlation with underwriter centrality measures and therefore we use the residuals from a regression of *LnOffer* on six lead IPO underwriter network centrality measures (*xLnOffer*) as a control variable in our regressions.

Our next two control variables are dummies for hi-tech (*HiTechDummy*) and VC-backed (*VCDummy*) IPOs. High technology firms as well as VC-backed firms tend to be younger, higher growth companies and therefore are expected to have a greater degree of uncertainty about their value. The final

[18] For robustness, we also used another measure of underwriter reputation as a control variable in our regressions, namely underwriter reputation as developed by Loughran and Ritter (2004) based on earlier work by Carter and Manaster (1990). This measure takes on values from 0 (least reputable underwriters) to 9 (most reputable underwriters). Our results using this alternative measure of underwriter reputation are similar to those reported here.

two control variables are either the raw return or absolute return on the CRSP value-weighted index between the filing date and the IPO issue date (*MktReturn* or *AbsMktReturn*, respectively) and the percentage difference between the original high filing price and original low filing price (*FilingWidth*). The greater the movement in the stock market between the filing date and the IPO issue date, the greater the likelihood of offer price revisions. Therefore we include *AbsMktReturn* to control for such market movement in regressions where we use *AbsRevision* as a dependent variable and include *MktReturn* as a control in regressions where we use *Revision* as a dependent variable. The greater the uncertainty about the value of IPO shares to be issued, the greater the filing range set by underwriters and we control for such uncertainty by including *FilingWidth* in our regressions. Similar control variables were used by Hanley (1993) and Lowry and Schwert (2004) in their investigations of the determinants of IPO offer price revision. Finally, we also include year and 2-digit SIC industry dummies to control for differences among IPO characteristics across different industries and time periods.

Our empirical results are presented in Table 2. Panel A of Table 2 reports our regressions with *AbsRevision* as the dependent variable. The number of observations in our regressions is reduced to 4,493 due to missing original filing high and low prices in the SDC database. All six lead IPO underwriter centrality measures have positive and statistically significant coefficient estimates indicating that more central lead IPO underwriters are less likely to set their initial pricing range closer to the eventual IPO offer price. This contradicts our information extraction hypothesis (**H1A**). These results hold even after controlling for underwriter reputation, which has positive and marginally significant coefficient estimates in three out of six regressions. Our regressions in Panel A of Table 2 also show that IPO offer price revisions either in a positive or a negative direction are more likely for younger, VC-backed, and hi-tech firms, and firms with larger original filing widths; in other words, firms which are likely to have a greater degree of uncertainty about their value. Finally, IPO offer price revisions are more likely if the stock market experiences relatively large movements between the filing and IPO issue dates.

Panel B of Table 2 reports our regressions with *Revision* as the dependent variable. All six lead IPO underwriter centrality measures have positive and statistically significant coefficient estimates indicating that more central lead IPO underwriters are better at disseminating favorable information about firms they take public and thus more likely to revise upwards the IPO offer price. This provides support for our information dissemination hypothesis (**H1B**). Further, Panel B of Table 2 shows that firms underwritten by more reputable underwriters, firms with larger offer sizes, and smaller firms are more likely to have their IPO offer prices revised in an upward direction. The remaining control variables have the same effect on *Revision* as on *AbsRevision* discussed above.

6.2. Underwriter Centrality and IPO Market Valuation

In this section we study the effect of lead IPO underwriter centrality on IPO market valuation by regressing IPO market valuation measures on underwriter centrality measures and other controls. We measure IPO market valuation using Tobin's Q, which is the ratio of the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and share price. We measure IPO market valuation by using the IPO offer price as the share price in the above definition (*QOP*). We also construct industry-adjusted Q ratio (*QOPAdj*) by subtracting contemporaneous 2-digit SIC code industry median Q ratio from the above proxy. The book value of assets and the book value of equity both for IPO firms and industry peers are taken from the first available post-IPO quarter on Compustat. The number of shares outstanding and the share price for industry peers is as of the end of the first available post-IPO quarter on Compustat. The number of shares outstanding for IPO firms is as of the first trading day.

In our regressions, we control for underwriter reputation, since we expect firms underwritten by higher reputation underwriters to receive higher valuations. We also control for IPO offer size as we expect firms raising more capital to have valuable investment projects, which, in its turn, should result in higher valuations. Further, we control for firm size and firm age as relatively younger and smaller firms are expected to have valuable growth opportunities and thus higher valuations. Next, we control for the proportion of secondary shares offered since, on the one hand, firms selling a larger proportion of secondary shares will raise less capital for investment and are likely to receive lower valuations, and on the other hand, insiders are likely to offer more secondary shares if they expect to receive relatively higher valuations for such shares. We also include *VCDummy* and *HiTechDummy* in our regressions since VC-backed and hi-tech firms are expected to have larger growth options and higher valuations. Finally, we also control for pre-IPO operating performance since better performing firms are expected to have higher valuations. We measure operating performance as the ratio of operating income before depreciation (OIBD) over the book value of assets at the end of the fiscal year prior to the IPO adjusted for the contemporaneous median OIBD/Assets of 2-digit SIC code industry peers (*OIBD/AssetsAdj*).

The results of our regressions with *QOPAdj* as the dependent variable are presented in Table 3. All six lead IPO underwriter centrality measurers have significantly positive coefficient estimates indicating that firms taken public by more central lead underwriters are able to obtain higher IPO market valuations. This provides support for our information dissemination hypothesis (**H2**), indicating that more central lead underwriters are able to disseminate information better. Our regressions in Table 3 also show that, as expected, smaller, younger, and VC-backed firms as well as those underwritten by higher reputation underwriters and those with larger offer sizes receive higher IPO market valuations. We also find that firms offering more secondary shares are associated with higher IPO market valuations.

6.3. Underwriter Centrality and IPO Initial Return

We study the effect of lead IPO underwriter centrality on IPO initial return by regressing *Underpricing* which is the percentage difference between the first trading day closing price and IPO offer price on our lead IPO underwriter centrality measures and other controls. We control for underwriter reputation by including *xMktShare* variable as described previously. Carter and Manaster (1991) predict that more reputable underwriters will underwrite less risky issues and less reputable underwriters will underwrite more risky issues and empirically document a negative relationship between underwriter reputation and underpricing.[19] Rock (1986) predicts a higher degree of underpricing for riskier firms due

[19] Although Carter and Manaster (1991) and Megginson and Weiss (1991) document a negative relationship between underwriter reputation and underpricing using the data from 1980s, later studies which make use of the data

to the higher costs investors need to incur to acquire information about such firms. Therefore we control for firm risk by including firm size (*LnAssets*), firm age (*LnAge*), *VCDummy*, and *HiTechDummy* as control variables. We also control for IPO offer size (*xLnOffer*) since this variable was shown to have a significant influence on underpricing in the previous literature.[20]

Further, we control for the percentage of secondary shares offered in the IPO (*Secondary*). On the one hand, Carter, Dark, and Singh (1998) predict and document a positive relationship between underpricing and the percentage of secondary shares offered using *Secondary* as a proxy for pre-offer demand. On the other hand, Aggarwal, Krigman, and Womack (2002) predict more underpricing for firms where managers retain more shares after the IPO; thus more secondary shares offered means less insider ownership after the IPO and less underpricing.[21] We also include the reciprocal of IPO offer price (1/*OfferPrice*) as a control variable. Beatty and Welch (1996) argue that, on the one hand, lower IPO offer prices increase brokerage commissions and analyst coverage and therefore may result in less underpricing; and, on the other hand, lower IPO offer prices increase the transaction costs of investors and therefore may result in more underpricing.[22] Next, we include *Revision* as a control variable since larger absolute price revisions indicate more information being generated during the waiting period which, in its turn, may affect IPO underpricing. We also control for the market movement in the pre-IPO period using the return on the CRSP value-weighted index over the 30-day period prior to the IPO (*PriorMktReturn*) to account for the flow of new information to the market prior to the IPO.[23] Lastly, we control for the "hot" and "cold" IPO markets documented in previous studies by including the average underpricing of all IPOs in the previous month (*AveUnderpricing*). Finally, in addition to year and industry dummies, we also include trading exchange dummies in our regressions.

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from 1990s and 2000s document a positive relationship between underwriter reputation and underpricing (see, among others, Aggarwal, Krigman, and Womack (2002) or Hanley and Hoberg (2012)).

[20] Loughran and Ritter (2004) document a negative relationship between underpricing and IPO offer size in the 1980s and the beginning of 2000s but a positive relationship in the 1990s.

[21] Aggarwal, Krigman, and Womack (2002) document an insignificantly negative relationship between IPO underpricing and the percentage of secondary shares sold at the IPO.

[22] Booth and Chua (1996) use IPO offer price as a proxy for information costs incurred to achieve secondary market liquidity and argue that IPOs with lower offer prices tend to have higher costs and therefore higher underpricing.

[23] Derrien and Womack (2003) show that pre-IPO market return is a significant determinant of IPO underpricing using French IPO data.

The results of our regressions are presented in Table 4. We find that four lead IPO underwriter centrality measures (*Degree*, *Outdegree*, *Betweenness*, and *Eigenvector*) have a positive and significant influence on IPO initial returns. This indicates that more central lead underwriters are likely to underprice their IPO issues more. This provides support for our hypothesis **H4B** according to which the effect of more centrally located lead underwriter on short-term secondary market valuation is stronger than its effect on IPO valuation. The number of observations in our regressions is reduced to 4,464 due to many missing *Revision* observations. We estimated our regressions also without *Revision* as a control variable which increased the number of observations to 5,794. The effect of underwriter centrality on IPO initial returns in such regressions was even stronger both in terms of the magnitude and the statistical significance; the coefficient estimates of *Degree, Outdegree, Betweenness, Eigenvector,* and *2-Stepreach* were positive and highly significant, and that of *Indegree* was also positive but not statistically significant.

We also find smaller IPO initial returns for larger and older firms which is consistent with the idea that riskier firms are likely to underprice more. We also find larger IPO initial returns for firms with more reputable underwriters, larger offer sizes, lower IPO offer prices, and higher pre-IPO market returns. Finally, higher average underpricing in the month prior to the IPO has a significantly positive effect on IPO initial returns suggesting a positive autocorrelation in initial returns and the existence of “hot” IPO markets.[24]

6.4. Underwriter Centrality and Secondary Market Valuation

In this section, we study the effect of underwriter centrality on secondary market valuations of IPO firms by regressing secondary market valuation measures on lead IPO underwriter centrality measures and other controls. We measure secondary market valuation using Tobin’s Q (described in section 6.2) with either the first trading day closing price as the share price in calculating the market value of assets (*QFTD*) or the share price at the end of the first post-IPO fiscal quarter (*QFQ*). We also

[24] Bradley and Jordan (2002) and Bradley, Cooney, Jordan, and Singh (2004) report similar results.

construct industry-adjusted Q ratios (*QFTDAdj* and *QFQAdj*) by subtracting contemporaneous 2-digit SIC code industry median Q ratios from the above proxies. The book value of assets and the book value of equity both for IPO firms and industry peers are taken from the first available post-IPO quarter on Compustat. The number of shares outstanding and the share price for industry peers is as of the end of the first available post-IPO quarter on Compustat. The number of shares outstanding for IPO firms is as of the first trading day.

The results of our regressions using *QFTDAdj* and *QFQAdj* as dependent variables are presented in Table 5. Our control variables are the same as when we study IPO market valuation. Similar to our findings in Table 3, all six lead IPO underwriter centrality measures have significantly positive coefficient estimates indicating that lead IPO underwriter centrality has a positive effect not only on IPO valuations but also on immediate secondary market valuations. This provides further support for our information dissemination hypothesis (**H3**). Further, the coefficient estimates of underwriter centrality measures are much larger in Table 5 than in Table 3 indicating that lead IPO underwriter centrality has a stronger effect on immediate secondary market valuations than on IPO valuations. This is consistent with our findings in section 6.3 on IPO initial returns and provides further support for our hypothesis **H4B**. Finally, we also find our control variables to have the same effect on secondary market valuations as on IPO market valuations, with one exception: we find that hi-tech firms and those with better pre-IPO operating performance receive higher valuations in the secondary market but not at the time of IPO.

6.5. Underwriter Centrality and the Participation of Financial Market Players in IPO

In this section we study how underwriter centrality affects the participation of financial market players, such as financial analysts and institutional investors, in the IPO in a multivariate regression setting. Our dependent variables are the number of analysts following the IPO firm at the end of the fiscal year of the issue as reported by IBES (*NumAn*), the number of institutional investors holding IPO firms' shares at the end of the first calendar quarter after the IPO (*InstN*), and the proportion of IPO firm shares held by institutional investors at the end of the first calendar quarter after the IPO (*InstP*).

Our independent variables are the six lead IPO underwriter centrality measures and other controls. We control for underwriter reputation since it is expected to positively influence the interest of financial market players. Next, we control for firm size, firm age, and offer size as larger and older firms as well as those making larger offers are expected to attract more interest from financial market players. We also control for the proportion of secondary shares offered in the IPO as more secondary shares offered may indicate greater pre-offer demand from investors, including institutions (see, e.g., Carter, Dark, and Singh (1998)). The next control variable we include is 1/*OfferPrice* since Brennan and Hughes (1991) show that the number of analysts following a firm is inversely related to its share price (see also Beatty and Welch (1996)). We also include *VCDummy*, *HiTechDummy*, and *Underpricing* as Bradley, Jordan, and Ritter (2003) show that analyst coverage initiation is more likely for IPO firms which are larger, VC-backed, and more underpriced.[25] Aggarwal, Krigman, and Womack (2002) also demonstrate that managers use underpricing as a strategic tool to generate information momentum, which, in its turn, positively affects research coverage and the demand for the stock (see also the information production model of Chemmanur (1993)). Finally, we also control for IPO firm secondary market valuation (*QFTDAdj*) and pre-issue operating performance (*OIBD*/*AssetsAdj*), since firms which receive higher valuations and perform better are likely to attract more interest from financial market players.

The results of our analysis are presented in Tables 6 and 7. Table 6 reports our findings regarding the number of analysts following the IPO firm. Since our dependent variable is a count variable we make use of Poisson maximum-likelihood estimation instead of OLS.[26] The coefficient estimates of lead IPO

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[25] Bradley, Jordan, and Ritter (2003) also find that analysts are somewhat more likely to initiate the coverage of firms in hi-tech industries.

[26] Since the number of analysts in our sample exhibits a certain degree of overdispersion (ranging between 1 to 24 with the mean of 3.13 and the median of 3), we also estimated our regressions using the negative binomial maximum-likelihood estimation technique as it is more appropriate for non-negative count data with overdispersion. The negative binomial model assumes the overdispersion parameter α to be greater than zero whereas the Poisson model assumes $\alpha = 0$. However, the likelihood ratio test in our negative binomial regressions could not reject the null hypothesis of $\alpha = 0$ (and thus our negative binomial estimation defaulted to Poisson estimation). Therefore, in Table 6 we make use of the Poisson maximum-likelihood estimation directly.

underwriter centrality measures are all positive and highly significant indicating that IPOs underwritten by more central underwriters are likely to be followed by more financial analysts post-IPO.[27]

Table 6 also shows that larger firms, firms with higher IPO valuations, those making larger offers and underwritten by higher reputation underwriters are followed by a greater number of financial analysts. Also, as expected, firms which are backed by VC, hi-tech firms, firms which are underpriced more, and those with lower offer prices are also followed by a greater number of financial analysts. Finally, younger firms are followed by a greater number of analysts as well. This last finding is perhaps due to the fact that VC-backed and hi-tech firms which receive more attention from financial analysts go public at a relatively younger age compared to other firms.

In Table 7 we report our findings on the participation of institutional investors in the IPO. For regressions with *InstN* as the dependent variable we make use of the negative binomial maximum-likelihood estimation technique since the number of institutional investors holding IPO firm shares is a count variable exhibiting a great degree of overdispersion (ranging between 1 to 259, with the mean of 22.05 and the median of 17). We find that all six lead IPO underwriter centrality measures have positive and highly significant coefficient estimates indicating that firms underwritten by more central underwriters are more likely to have a greater number of institutional investors holding their shares post-IPO as well as more likely to have a greater proportion of their shares held by institutional investors post-IPO.[28] These findings provide support for our hypothesis **H5** indicating that more central lead IPO underwriters are able to disseminate information better.

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[27] The number of observations in our regressions is 4,018 since many firms in our sample are missing financial analyst data in IBES at the end of the fiscal year of the IPO. As a robustness test, we assumed that such firms are not covered by financial analysts and set *NumAn* equal to zero for such firms. Then we re-estimated our regressions with this alternative definition of *NumAn* (with 5,342 observations). The results were similar (and somewhat stronger) to those reported in Table 6; all six lead IPO underwriter centrality measures had positive and highly significant coefficient estimates.

[28] As a robustness test we set *InstN* and *InstP* equal to zero for those firms which do not have institutional investor data available in the Thomson Reuters institutional (13F) holdings database (basically assuming that institutional investors do not hold shares of such firms). We then re-estimated our regressions with these alternative definitions of *InstN* and *InstP* (this increases the number of observations in our regressions from 4,900 to 5,342). The results of these regressions were similar to those reported in Table 7; all six lead IPO underwriter centrality measures had positive and highly significant coefficient estimates both in *InstN* and *InstP* regressions.

Our findings in Table 7 also show that underwriter reputation has a somewhat positive effect on the number of institutional investors holding IPO firm shares but a somewhat negative effect on the proportion of shares held by institutional investors.[29] Our findings also show, as expected and consistent with other studies in the literature, positive and significant coefficient estimates for the offer size, firm size, the proportion of secondary shares offered, VC-backed dummy, and underpricing both in the *InstN* and *InstP* regressions. Further, we find institutional investors are more likely to hold a smaller proportion of shares of younger firms, hi-tech firms, and firms with higher IPO valuations. At the same time we find hi-tech firms and firms with lower IPO offer prices to be associated with a greater number of institutional investors holding their shares post-IPO.

6.6. Underwriter Centrality and the Post-Issue Stock Return Performance of IPO Firms

In this section we study the effect of underwriter centrality on the post-issue stock return performance of IPO firms by regressing 1*YearHPRAdj* on our six lead IPO underwriter centrality measures and other controls. 1*YearHPRAdj* is the IPO firm's post-issue one-year holding period return calculated by compounding daily returns over 252 trading days after the IPO (excluding the first trading day's return) adjusted for (minus) the holding period return of the NASDAQ value-weighted index over the same period. If an IPO firm is delisted before the end of the one-year period, returns of the IPO firm and NASDAQ value-weighted index are compounded until the delisting date.

We control for underwriter reputation given that Carter, Dark, and Singh (1998) find underwriter reputation to have a positive effect on long-run post-IPO returns. Our control variables also include offer size, firm age, and underpricing since Ritter (1991) documents a somewhat positive effect of offer size and firm age on the post-issue long-run performance of IPO firms and a somewhat negative effect of underpricing on the same performance. We also include firm size and VC dummy as control variables as Brav and Gompers (1997) find a better post-IPO long-run stock return performance for larger firms and

[29] Aggarwal, Prabhala, and Puri (2002) also report a significantly negative relationship between underwriter reputation and the proportion of IPO shares allocated to institutions in a sample of IPOs in 1997-1998.

VC-backed firms. Finally, we also include hi-tech dummy and IPO valuation variables as controls since these variables may potentially affect post-IPO stock return performance as well.

The results of our regressions are presented in Table 8. Five out of six lead IPO underwriter centrality measures (except 2-*StepReach*) have positive and statistically significant coefficient estimates. This indicates that lead IPO underwriter centrality has a positive influence on the one-year post-IPO market-adjusted stock return performance of firms going public. We estimated our regressions also using post-IPO three-month and six-month stock return performance and found lead IPO underwriter centrality to have a significantly positive effect on such short-run performance. Then we estimated our regressions using two-year, three-year, and five-year stock return performance, but did not find lead IPO underwriter centrality to have a statistically significant effect on such long-run performance. Thus, our findings suggest that lead IPO underwriter centrality positively affects post-IPO stock return performance up to one year after going public; however this positive effect disappears for longer than 1 year stock returns. This provides partial support for our hypothesis **H6**, since our results indicate that the ability of more central lead underwriters to disseminate information better has a positive effect on IPO firm returns up to one year after going public.

Our results in Table 8 also show that larger firms and hi-tech firms realize significantly better post-IPO market-adjusted stock returns compared to other firms, whereas the stock returns of firms with larger IPO offer sizes are significantly worse.[30]

6.7. Instrumental Variable Analysis of the Effect of Underwriter Centrality on IPOs

We showed above that lead IPO underwriter centrality has a significant effect on various characteristics of firms going public (such as IPO characteristics, IPO and secondary market valuation, the participation of financial market players, as well as post-IPO stock return performance). However, it can be argued that there may be endogenous matching between lead IPO underwriter centrality and the

[30] Krishnan, Ivanov, Masulis, and Singh (2011) also report a somewhat negative relationship between IPO offer size and post-IPO long-run returns for a sample of IPOs in 1993-2004.

characteristics of IPO firms. In other words, firms of higher quality are likely to attract more central lead underwriters. If this is the case, then our results may be due to the higher quality of firms taken public by more central lead underwriters rather than lead underwriter centrality itself. In such a case our OLS analysis would suffer from a potential endogeneity problem where lead underwriter centrality measures may be correlated with error terms making our OLS coefficient estimates biased.

A common solution used in the literature to deal with endogeneity problems is to employ the two-stage least squares (2SLS) methodology and make use of instrumental variables to generate exogenous variation in endogenous variables. However, an instrumental variable estimation presents several challenges. First, finding good instruments is rather difficult since they should have a relatively high correlation with endogenous variables and should be virtually uncorrelated with IPO firm characteristics that we study (i.e., should satisfy the exclusion restriction). In other words, the instruments used should not suffer from the same endogeneity problem as our endogenous variables. Second, 2SLS can be less efficient than OLS when it generates relatively large standard errors (Wooldridge, 2010, page 111).

We construct a categorical variable for the repeal of the Glass-Steagall Act in 1999 and use it as our instrument for underwriter centrality in our analysis. The repeal of the Glass-Steagall Act essentially opened the door for commercial banks to enter the market of securities underwriting business and, in particular, the IPO market.[31] The greater number of underwriting institutions in the IPO market itself would create greater opportunities for such institutions to establish new connections and expand their respective networks. This, in turn, could potentially affect the centrality position within the network of underwriting institutions of both existing investment banks in the IPO market as well as the new commercial banks entering the IPO market.[32]

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[31] On November 12, 1999 the Gramm-Leach-Bliley Act was enacted which repealed part of the Glass-Steagall Act which prohibited any one institution from acting as any combination of an investment bank, a commercial bank, and an insurance company. Thus it removed barriers in the market among commercial banks, investment banks, securities firms, and insurance companies and allowed such institutions to consolidate.

[32] In principle, the entrance of new banks (previously restricted from IPO underwriting due to their commercial banking activities by the Glass-Steagall Act) into the IPO underwriting market may either increase or decrease the centrality position of lead IPO underwriters. To give an example, the measure *Degree* is defined as "the number of connections formed" over "the number of possible connections," and we would expect both the numerator and

Given that our underwriter centrality measures are computed using the data from the previous five years, we construct our instrumental variable (denoted as *GS*) as a categorical variable taking values 0, 1, and 2 for IPO firms which went public in 1980-1999, 2000-2004, and 2005-2009, respectively. Thus, a value of 0 indicates IPO firms whose lead underwriters' centrality is measured only using the data from before the repeal of the Glass-Steagall Act, a value of 1 indicates IPO firms whose lead underwriters' centrality is measured using the data both from before and after the repeal of the Glass-Steagall Act, and a value of 2 indicates IPO firms whose lead underwriters' centrality is measured only using the data from after the repeal of the Glass-Steagall Act. Thus, we expect the centrality of institutions underwriting IPOs to be positively correlated with *GS*. At the same time we do not expect any significant relationship between *GS* and the characteristics (quality) of firms that went public during our sample period (thus satisfying the exclusion restriction). Thus, using the above instrument, we seek to establish a causal relationship between lead IPO underwriter centrality and IPO characteristics.

The results of our instrumental variable estimation are presented in Table 9. To conserve space, we present here our instrumental variable analysis using only one measure of lead IPO underwriter centrality, namely, *Degree* (our untabulated results using other measures of lead IPO underwriter centrality are similar to those reported here for *Degree*). Due to multicollinearity concerns, we drop year dummies from our estimation since our instrument itself is essentially a time indicator. For each dependent variable that we study, we present both first and second stage regressions of our 2SLS estimation. Regressions 1, 3, 5, and 7 in Panels A and B of Table 9 present first stage regressions of *GS* and other control variables on *Degree*. The coefficient estimates of *GS* are positive and highly significant indicating a strong positive correlation between *GS* and *Degree* centrality. This suggests that, on average, lead IPO underwriter centrality significantly increased after the repeal of the Glass-Steagall Act. These

denominator of *Degree* to increase after the repeal of the Act. However, if the majority of new underwriters entering the IPO underwriting market form connections with the existing underwriters, then we can expect the centrality of lead IPO underwriters as measured by *Degree* to increase after the repeal of the act. This is what seems to have happened after the repeal of the Glass-Steagall Act: our empirical findings presented here indicate that the average *Degree* centrality of lead IPO underwriters indeed increased significantly from the period before the Glass-Steagall Act was repealed to the period after the repeal. The above points are broadly true not only for *Degree* centrality but also for our other centrality measures.

regressions also report the F-statistic of the weak instruments test (or the test of excluded instruments). This test is used to determine whether instrumental variables used in first stage regressions are strong. In their survey of the literature on weak instruments, Stock, Wright, and Yogo (2002) develop benchmarks for the necessary magnitude of the F-statistic. They indicate that if the number of instruments is equal to one, then the critical value of the F-statistic is 8.96. Since the F-statistics reported for all first stage regressions are highly significant and well above the critical value (except in *AbsRevision* estimation where F-statistic is equal 6.60), the null hypothesis that our instrument is weak is strongly rejected.

Our second stage regressions indicate that, even after controlling for the potential endogenous matching between lead IPO underwriter centrality and firm quality, lead IPO underwriter centrality still has a significantly positive effect on the absolute value of offer price revision (*AbsRevision*), both IPO and secondary market valuation (*QOPAdj* and *QFTDAdj*), the number of analysts following the firm (*LnNumAn*), and the number of institutional investors holding IPO firm shares (*LnInstN*).[33] The coefficient estimates of *DegreeHat* (the predicted values of *Degree* from the first stage) are highly significant. These results are consistent with our findings in the previous sections, and indicate that the relationships between *Degree* centrality and the above IPO variables are causal. We, however, do not find a significant relationship between lead IPO underwriter centrality and IPO initial return (*Underpricing*) and post-IPO stock return performance (1*YearHPRAdj*) in the second stage of our instrumental variable analysis.

7. Conclusion

Using various SNA measures, we analyze, for the first time in the literature, how various IPO characteristics are affected by the location of the lead IPO underwriter in the network of investment banks generated by their participation in IPO underwriting syndicates. We hypothesize that investment banking networks perform two possible information-related roles during the IPO process: an information

[33] Since in the second stage of 2SLS we cannot implement Poisson or negative binomial maximum-likelihood estimations and need to run OLS regressions, we use the natural logarithm of one plus *NumAn* (*LnNumAn*) and *InstN* (*LnInstN*) as our dependent variables in 2SLS estimation instead of *NumAn* and *InstN*.

extraction role, where its investment banking network helps the lead IPO underwriter extract credible information useful in pricing the IPO from various institutional investors; or an information dissemination role, where the lead underwriter is able to use its investment banking network to credibly convey its favorable private information about the IPO firm to various institutional investors.

Our empirical results are consistent with our hypotheses and can be summarized as follows. First, we find that IPOs underwritten by lead underwriters who are positioned more centrally in their respective investment banking networks are associated with larger IPO offer price revisions. This indicates that, overall, the information dissemination role of investment banking networks dominates the information extraction role, at least in this early stage in the IPO process. Second, IPOs underwritten by lead underwriters who are positioned more centrally in their investment banking networks are also associated with greater IPO and secondary market valuations, and greater initial IPO returns. Third, IPO firms which are underwritten by more central lead underwriters generate greater interest on the part of financial market players; in the sense that such firms are followed by a greater number of financial analysts and have larger institutional investor holdings. Finally, IPO firms underwritten by more central lead underwriters realize better post-IPO long-run (six-months and one-year) stock returns. The first three results above are also confirmed by our instrumental variable analysis, which allows us to control for the potential endogenous matching between lead underwriter centrality and the characteristics of IPO firms.

In general, our results are consistent with the notion that lead IPO underwriters more centrally located within investment banking networks are able to more credibly and efficiently disseminate their favorable private information about the firm they are taking public to the investment banks in their network, and through them, to the institutional investors that each investment bank may repeatedly interact with (in IPO as well as non-IPO related service contexts).

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Table 1. Summary statistics

The sample consists of IPOs conducted in 1980-2009. Degree, Indegree, Outdegree, Betweenness, Eigenvector, and 2-StepReach are measures of lead IPO underwriter centrality as described in section 5. AbsRevision is the absolute percentage difference between the IPO offer price and the midpoint of original filing range. Revision is the percentage difference between the IPO offer price and the midpoint of original filing range. QOPAdj, QFTDAdj, and QFQAdj are the industry-adjusted Tobin's Q ratio calculated using the IPO offer price, the first trading day closing price, and the price at the end of the first post-IPO fiscal quarter, respectively. Tobin's Q is the ratio of the market value of assets to the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the share price. The number of shares outstanding for IPO firms is as of the first trading day and the share price is the IPO offer price (for QOPAdj), the first trading day closing price (for QFTDAdj), or the price at the end of the first post-IPO fiscal quarter (for QFQAdj). The number of shares outstanding and the share price for industry peers is taken from the first available post-IPO quarter on Compustat. The book value of assets and the book value of equity both for IPO firms and industry peers are taken from the first available post-IPO quarter on Compustat. Industry adjustment is performed by subtracting the contemporaneous median Tobin's Q of IPO firm's 2-digit SIC code industry peers. Underpricing is the percentage difference between the first trading day closing price and IPO offer price. NumAn is the number of analysts following the firm at the end of the fiscal year of IPO. InstN is the number of institutional investors holding IPO firm shares at the end of the first calendar quarter after IPO. InstP is the proportion of IPO firm shares held by institutional investors at the end of the first calendar quarter after IPO. 1YearHPRAdj is the IPO firms' one-year holding period return calculated by compounding daily returns over 252 trading days after the IPO (excluding the first trading day's return) adjusted for (minus) the holding period return of the NASDAQ value-weighted index over the same period. If an IPO firm is delisted before the end of the one-year period, returns of the IPO firm and NASDAQ value-weighted index are compounded until the delisting date. MktShare is the lead underwriter's share of total proceeds raised in the IPO market in the previous five years. LnOffer is the natural logarithm of the IPO issue offer size. LnAssets is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. LnAge is the natural logarithm of one plus the number of years from IPO firm founding year to the IPO issue year. VCDummy is a dummy equal to one for VC-backed IPOs. HiTechDummy is a dummy equal to one for Hi-Tech IPOs. AbsMktReturn is the absolute return on the CRSP value-weighted index between the filing date and the IPO issue date. MktReturn is the return on the CRSP value-weighted index between the filing date and the IPO issue date. FilingWidth is the percentage difference between the original high filing price and original low filing price. Secondary is the percentage of secondary shares offered in the IPO. 1/OfferPrice is the reciprocal of IPO offer price. OIBD/AssetsAdj is the operating income before depreciation over the book value of assets at the end of the fiscal year prior to IPO adjusted for the contemporaneous median OIBD/Assets of 2-digit SIC code industry peers. PriorMktReturn is the return on the CRSP value-weighted index over the 30-day period prior to the IPO. AveUnderpricing is the average underpricing of all IPOs in the previous month.

	N	Minimum	Mean	Median	Maximum	St.Dev.
Lead IPO Underwriter Centrality Measures						
Degree	6,217	0	0.106	0.072	0.483	0.114
Indegree	6,217	0	0.032	0.034	0.154	0.029
Outdegree	6,217	0	0.094	0.039	0.473	0.115
Betweenness	6,217	0	0.026	0.008	0.400	0.039
Eigenvector	6,217	0	0.102	0.104	0.569	0.093
2-Stepreach	6,217	0	0.438	0.559	0.926	0.338
IPO Characteristics						
AbsRevision	4,671	0	0.136	0.091	3.444	0.157
Revision	4,671	-0.833	-0.001	0	3.444	0.208
QOPAdj	5,823	-3.049	1.139	0.644	67.870	2.801
QFTDAdj	5,823	-2.549	1.889	0.911	120.983	4.494
QFQAdj	5,766	-3.376	1.970	0.922	96.939	4.322
Underpricing	6,107	-70.455	20.369	7.692	697.500	42.290
NumAn	4,267	1	3.135	3	24	2.097
InstN	5,476	1	22.049	17	259	20.266
InstP	5,474	0	0.211	0.174	1	0.175
1YearHPRAdj	6,206	-1.867	-0.050	-0.198	11.912	0.842
Control Variables						
MktShare	6,217	0	0.028	0.009	0.215	0.040
LnOffer	6,217	12.930	16.984	17.059	22.199	1.254
LnAssets	5,875	0	16.749	16.691	23.645	1.861
LnAge	6,175	0	2.137	2.079	5.112	0.975
VCDummy	6,217	0	0.428	0	1	0.495
HiTechDummy	6,217	0	0.522	1	1	0.500
AbsMktReturn	5,676	0	0.051	0.037	0.870	0.054
MktReturn	5,676	-0.310	0.034	0.028	0.870	0.066
FilingWidth	4,670	0	0.166	0.167	2	0.104
Secondary	6,217	0	11.070	0	100	19.268
1/OfferPrice	6,217	0.010	0.196	0.091	100	1.572
OIBD/AssetsAdj	5,535	-125.732	-0.192	0.023	6.157	1.860
PriorMktReturn	6,217	-0.291	0.014	0.015	0.183	0.037
AveUnderpricing	6,201	-7.4	21.208	14.1	121.4	21.799

Table 2. Relationship between lead IPO underwriter centrality and offer price revision

The sample consists of IPOs conducted in 1980-2009. Degree, Indegree, Outdegree, Betweenness, Eigenvector, and 2-StepReach are measures of lead IPO underwriter centrality as described in section 5. MktShare is the lead underwriter's share of total proceeds raised in the IPO market in the previous five years. xMktShare is the residuals from a regression of MktShare on six lead IPO underwriter centrality measures. LnOffer is the natural logarithm of the IPO issue offer size. xLnOffer is the residuals from a regression of LnOffer on six lead IPO underwriter centrality measures. LnAssets is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. LnAge is the natural logarithm of one plus the number of years from IPO firm founding year to the IPO issue year. VCDummy is a dummy equal to one for VC-backed IPOs. HiTechDummy is a dummy equal to one for Hi-Tech IPOs. FilingWidth is the percentage difference between the original high filing price and original low filing price. All regressions include year and 2-digit SIC industry code dummies. *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Relationship between lead IPO underwriter centrality and absolute value of offer price revision

AbsRevision is the absolute percentage difference between the IPO offer price and the midpoint of original filing range. AbsMktReturn is the absolute return on the CRSP value-weighted index between the filing date and the IPO issue date.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	AbsRevision	AbsRevision	AbsRevision	AbsRevision	AbsRevision	AbsRevision
Intercept	-0.094	-0.143	-0.107	-0.146	-0.067	-0.079
	(-0.96)	(-1.47)	(-1.10)	(-1.50)	(-0.69)	(-0.81)
Degree	0.186					
	(6.25)***					
Indegree		0.447				
		(4.76)***				
Outdegree			0.166			
			(5.65)***			
Betweenness				0.242		
				(3.85)***		
Eigenvector					0.222	
					(7.46)***	
2-Stepreach						0.075
						(7.37)***
xMktShare	0.198	0.153	0.197	-0.005	0.184	0.004
	(1.78)*	(0.92)	(1.78)*	(-1.39)	(1.66)*	(1.15)
xLnOffer	0.001	-0.003	-0.000	0.194	0.001	0.147
	(0.28)	(-1.38)	(-0.10)	(1.74)*	(0.21)	(1.32)
LnAssets	0.000	0.003	0.001	0.004	-0.001	-0.002
	(0.17)	(1.86)*	(0.69)	(2.20)**	(-0.38)	(-0.84)
LnAge	-0.007	-0.008	-0.007	-0.007	-0.007	-0.008
	(-2.77)***	(-3.11)***	(-2.74)***	(-2.88)***	(-2.84)***	(-3.06)***
VCDummy	0.032	0.032	0.033	0.035	0.029	0.028
	(6.37)***	(6.37)***	(6.59)***	(7.09)***	(5.71)***	(5.63)***
HiTechDummy	0.020	0.020	0.020	0.021	0.018	0.018
	(3.04)***	(3.03)***	(3.13)***	(3.31)***	(2.72)***	(2.74)***
AbsMktReturn	0.237	0.232	0.233	0.225	0.235	0.249
	(5.20)***	(5.08)***	(5.11)***	(4.92)***	(5.16)***	(5.45)***
FilingWidth	0.354	0.344	0.357	0.353	0.346	0.339
	(16.32)***	(15.79)***	(16.42)***	(16.22)***	(15.96)***	(15.62)***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1831	0.1801	0.1818	0.1786	0.1862	0.1859
N	4,493	4,493	4,493	4,493	4,493	4,493

Table 2. Relationship between lead IPO underwriter centrality and offer price revision (continued)

Panel B: Relationship between lead IPO underwriter centrality and offer price revision
Revision is the percentage difference between the IPO offer price and the midpoint of original filing range. MktReturn is the return on the CRSP value-weighted index between the filing date and the IPO issue date.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Revision	Revision	Revision	Revision	Revision	Revision
Intercept	0.492	0.274	0.484	0.344	0.425	0.428
	(3.85)***	(2.12)**	(3.80)***	(2.68)***	(3.29)***	(3.32)***
Degree	0.529					
	(13.57)***					
Indegree		0.584				
		(4.67)***				
Outdegree			0.537			
			(14.02)***			
Betweenness				0.722		
				(8.68)***		
Eigenvector					0.381	
					(9.67)***	
2-Stepreach						0.141
						(10.56)***
xMktShare	0.585	0.066	0.084	0.573	0.546	0.082
	(4.02)***	(14.69)***	(4.05)***	(15.83)***	(16.52)***	(3.25)***
xLnOffer	0.085	0.507	0.588	0.069	0.074	0.477
	(18.52)***	(3.42)***	(18.56)***	(3.89)***	(3.72)***	(17.35)***
LnAssets	-0.030	-0.017	-0.029	-0.020	-0.025	-0.028
	(-12.25)***	(-7.30)***	(-12.21)***	(-8.89)***	(-10.12)***	(-10.92)***
LnAge	-0.003	-0.006	-0.003	-0.004	-0.004	-0.005
	(-0.99)	(-1.60)	(-0.84)	(-1.23)	(-1.28)	(-1.56)
VCDummy	0.003	0.010	0.004	0.012	0.002	0.000
	(0.40)	(1.43)	(0.65)	(1.85)*	(0.33)	(0.04)
HiTechDummy	0.018	0.021	0.019	0.023	0.016	0.016
	(2.08)**	(2.42)**	(2.19)**	(2.63)***	(1.92)*	(1.86)*
MktReturn	0.337	0.309	0.334	0.319	0.317	0.333
	(6.71)***	(6.05)***	(6.67)***	(6.29)***	(6.25)***	(6.59)***
FilingWidth	0.138	0.119	0.148	0.135	0.119	0.106
	(4.84)***	(4.11)***	(5.21)***	(4.70)***	(4.16)***	(3.68)***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2061	0.1770	0.2083	0.1869	0.1901	0.1934
N	4,493	4,493	4,493	4,493	4,493	4,493

Table 3. Relationship between lead IPO underwriter centrality and IPO market valuation

The sample consists of IPOs conducted in 1980-2009. Degree, Indegree, Outdegree, Betweenness, Eigenvector, and 2-StepReach are measures of lead IPO underwriter centrality as described in section 5. QOPAdj is the industry-adjusted Tobin's Q ratio calculated using the IPO offer price. Tobin's Q is the ratio of the market value of assets to the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the share price. The number of shares outstanding for IPO firms is as of the first trading day and the share price is the IPO offer price. The number of shares outstanding and the share price for industry peers is taken from the first available post-IPO quarter on Compustat. The book value of assets and the book value of equity both for IPO firms and industry peers are taken from the first available post-IPO quarter on Compustat. Industry adjustment is performed by subtracting the contemporaneous median Tobin's Q of IPO firm's 2-digit SIC code industry peers. MktShare is the lead underwriter's share of total proceeds raised in the IPO market in the previous five years. xMktShare is the residuals from a regression of MktShare on six lead IPO underwriter centrality measures. LnOffer is the natural logarithm of the IPO issue offer size. xLnOffer is the residuals from a regression of LnOffer on six lead IPO underwriter centrality measures. LnAssets is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. LnAge is the natural logarithm of one plus the number of years from IPO firm founding year to the IPO issue year. Secondary is the percentage of secondary shares offered in the IPO. VCDummy is a dummy equal to one for VC-backed IPOs. HiTechDummy is a dummy equal to one for Hi-Tech IPOs. OIBD/AssetsAdj is the operating income before depreciation over the book value of assets at the end of the fiscal year prior to IPO adjusted for the contemporaneous median OIBD/Assets of 2-digit SIC code industry peers. All regressions include year dummies. *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	QOPAdj	QOPAdj	QOPAdj	QOPAdj	QOPAdj	QOPAdj
Intercept	11.239	8.807	11.114	9.508	10.341	11.014
	(11.67)***	(9.37)***	(11.59)***	(10.15)***	(10.80)***	(11.23)***
Degree	4.907					
	(10.44)***					
Indegree		6.603				
		(4.22)***				
Outdegree			4.789			
			(10.50)***			
Betweenness				8.138		
				(7.67)***		
Eigenvector					4.267	
					(8.34)***	
2-StepReach						1.553
						(8.54)***
xMktShare	3.788	4.556	3.773	4.357	4.653	4.154
	(2.48)**	(2.96)***	(2.47)**	(2.84)***	(3.04)***	(2.71)***
xLnOffer	0.544	0.319	0.528	0.370	0.417	0.528
	(9.22)***	(5.78)***	(9.09)***	(6.83)***	(7.50)***	(8.57)***
LnAssets	-0.615	-0.464	-0.606	-0.516	-0.561	-0.596
	(-18.40)***	(-15.47)***	(-18.43)***	(-16.91)***	(-17.21)***	(-17.17)***
LnAge	-0.075	-0.105	-0.073	-0.096	-0.091	-0.090
	(-1.68)*	(-2.35)**	(-1.64)	(-2.14)**	(-2.03)**	(-2.03)**
Secondary	0.005	0.005	0.005	0.006	0.004	0.003
	(2.29)**	(2.52)**	(2.65)***	(3.10)***	(1.88)*	(1.61)
VCDummy	0.163	0.201	0.180	0.229	0.123	0.112
	(1.97)**	(2.39)**	(2.18)**	(2.77)***	(1.46)	(1.33)
HiTechDummy	-0.039	0.023	-0.028	0.021	-0.048	-0.052
	(-0.45)	(0.27)	(-0.33)	(0.24)	(-0.57)	(-0.61)
OIBD/AssetsAdj	-0.007	-0.020	-0.007	-0.016	-0.011	-0.008
	(-0.35)	(-1.01)	(-0.37)	(-0.79)	(-0.56)	(-0.43)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0979	0.0825	0.0981	0.0895	0.0913	0.0919
N	5,342	5,342	5,342	5,342	5,342	5,342

Table 4. Relationship between lead IPO underwriter centrality and IPO initial return

The sample consists of IPOs conducted in 1980-2009. Degree, Indegree, Outdegree, Betweenness, Eigenvector, and 2-StepReach are measures of lead IPO underwriter centrality as described in section 5. Underpricing is the percentage difference between the first trading day closing price and IPO offer price. MktShare is the lead underwriter's share of total proceeds raised in the IPO market in the previous five years. xMktShare is the residuals from a regression of MktShare on six lead IPO underwriter centrality measures. LnOffer is the natural logarithm of the IPO issue offer size. xLnOffer is the residuals from a regression of LnOffer on six lead IPO underwriter centrality measures. LnAssets is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. LnAge is the natural logarithm of one plus the number of years from IPO firm founding year to the IPO issue year. Secondary is the percentage of secondary shares offered in the IPO. 1/OfferPrice is the reciprocal of IPO offer price. VCDummy is a dummy equal to one for VC-backed IPOs. HiTechDummy is a dummy equal to one for Hi-Tech IPOs. AbsRevision is the absolute percentage difference between the IPO offer price and the midpoint of original filing range. PriorMktReturn is the return on the CRSP value-weighted index over the 30-day period prior to the IPO. AveUnderpricing is the average underpricing of all IPOs in the previous month. All regressions include year, 2-digit SIC industry code, and trading exchange dummies. *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Underpricing	Underpricing	Underpricing	Underpricing	Underpricing	Underpricing
Intercept	44.828	23.547	46.488	35.656	31.969	29.294
	(1.89)*	(0.99)	(1.97)**	(1.51)	(1.34)	(1.23)
Degree	47.852					
	(6.92)***					
Indegree		-22.436				
		(-1.02)				
Outdegree			53.381			
			(7.92)***			
Betweenness				69.556		
				(4.87)***		
Eigenvector					15.328	
					(2.21)**	
2-Stepreach						3.925
						(1.58)
xMktShare	108.554	106.889	109.477	107.825	105.089	103.076
	(4.41)***	(4.31)***	(4.45)***	(4.37)***	(4.25)***	(4.16)***
xLnOffer	3.740	0.831	3.927	2.265	1.797	1.818
	(4.51)***	(1.06)	(4.81)***	(2.92)***	(2.24)**	(2.10)**
LnAssets	-2.300	-0.914	-2.370	-1.646	-1.450	-1.374
	(-5.36)***	(-2.23)**	(-5.61)***	(-4.03)***	(-3.36)***	(-3.10)***
LnAge	-1.901	-2.154	-1.850	-2.026	-2.079	-2.115
	(-3.25)***	(-3.67)***	(-3.17)***	(-3.46)***	(-3.54)***	(-3.61)***
Secondary	-0.046	-0.025	-0.040	-0.032	-0.039	-0.038
	(-1.58)	(-0.83)	(-1.38)	(-1.11)	(-1.33)	(-1.29)
1/OfferPrice	3.474	3.352	3.460	3.412	3.414	3.418
	(6.31)***	(6.06)***	(6.30)***	(6.18)***	(6.17)***	(6.17)***
VCDummy	0.293	1.437	0.269	0.985	0.837	0.967
	(0.26)	(1.26)	(0.24)	(0.87)	(0.73)	(0.84)
HiTechDummy	-0.964	-0.429	-0.929	-0.612	-0.771	-0.692
	(-0.67)	(-0.30)	(-0.65)	(-0.42)	(-0.53)	(-0.48)
AbsRevision	48.939	50.897	48.964	49.879	49.926	50.138
	(15.00)***	(15.53)***	(15.04)***	(15.27)***	(15.19)***	(15.25)***
PriorMktReturn	79.676	79.703	80.030	80.533	79.009	78.895
	(5.59)***	(5.56)***	(5.63)***	(5.64)***	(5.52)***	(5.51)***
AveUnderpricing	0.361	0.377	0.360	0.372	0.371	0.370
	(7.13)***	(7.39)***	(7.12)***	(7.32)***	(7.28)***	(7.26)***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Exch. Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2851	0.2774	0.2875	0.2812	0.2781	0.2777
N	4,464	4,464	4,464	4,464	4,464	4,464

Table 5. Relationship between lead IPO underwriter centrality and secondary market valuation

The sample consists of IPOs conducted in 1980-2009. Degree, Indegree, Outdegree, Betweenness, Eigenvector, and 2-StepReach are measures of lead IPO underwriter centrality as described in section 5. QFTDAdj and QFQAdj are the industry-adjusted Tobin's Q ratios calculated using the first trading day closing price and the price at the end of the first post-IPO fiscal quarter, respectively. Tobin's Q is the ratio of the market value of assets to the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the share price. The number of shares outstanding for IPO firms is as of the first trading day and the share price is the first trading day closing price (for QFTDAdj) or the price at the end of the first post-IPO fiscal quarter (for QFQAdj). The number of shares outstanding and the share price for industry peers is taken from the first available post-IPO quarter on Compustat. The book value of assets and the book value of equity both for IPO firms and industry peers are taken from the first available post-IPO quarter on Compustat. Industry adjustment is performed by subtracting the contemporaneous median Tobin's Q of IPO firm's 2-digit SIC code industry peers. MktShare is the lead underwriter's share of total proceeds raised in the IPO market in the previous five years. xMktShare is the residuals from a regression of MktShare on six lead IPO underwriter centrality measures. LnOffer is the natural logarithm of the IPO issue offer size. xLnOffer is the residuals from a regression of LnOffer on six lead IPO underwriter centrality measures. LnAssets is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. LnAge is the natural logarithm of one plus the number of years from IPO firm founding year to the IPO issue year. Secondary is the percentage of secondary shares offered in the IPO. VCDummy is a dummy equal to one for VC-backed IPOs. HiTechDummy is a dummy equal to one for Hi-Tech IPOs. OIBD/AssetsAdj is the operating income before depreciation over the book value of assets at the end of the fiscal year prior to IPO adjusted for the contemporaneous median OIBD/Assets of 2-digit SIC code industry peers. All regressions include year dummies. *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Dependent	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
variable	QFTDAdj	QFTDAdj	QFTDAdj	QFTDAdj	QFTDAdj	QFTDAdj	QFQAdj	QFQAdj	QFQAdj	QFQAdj	QFQAdj	QFQAdj
Intercept	15.338	10.557	15.183	12.062	13.190	14.478	13.399	8.740	13.258	10.160	11.275	12.280
	(10.11)***	(7.11)***	(10.06)***	(8.16)***	(8.72)***	(9.36)***	(9.27)***	(6.15)***	(9.22)***	(7.19)***	(7.81)***	(8.32)***
Degree	8.725						8.801					
	(11.79)***						(12.84)***					
Indegree		8.018						9.197				
		(3.24)***						(4.00)***				
Outdegree			8.620						8.726			
			(12.01)***						(13.12)***			
Betweenness				13.399						14.033		
				(8.01)***						(8.99)***		
Eigenvector					6.584						6.722	
					(8.15)***						(8.98)***	
2-Stepreach						2.524						2.402
						(8.80)***						(9.06)***
xMktShare	14.170	15.598	14.123	15.222	15.711	14.899	12.352	13.886	12.293	13.472	13.957	13.202
	(5.90)***	(6.42)***	(5.88)***	(6.30)***	(6.50)***	(6.17)***	(5.54)***	(6.15)***	(5.52)***	(6.00)***	(6.22)***	(5.88)***
xLnOffer	0.854	0.407	0.833	0.528	0.586	0.781	0.718	0.284	0.699	0.398	0.451	0.619
	(9.21)***	(4.67)***	(9.11)***	(6.17)***	(6.67)***	(8.04)***	(8.38)***	(3.52)***	(8.28)***	(5.04)***	(5.56)***	(6.89)***
LnAssets	-0.837	-0.543	-0.826	-0.649	-0.709	-0.777	-0.709	-0.420	-0.698	-0.524	-0.581	-0.631
	(-15.93)***	(-11.44)***	(-15.97)***	(-13.48)***	(-13.76)***	(-14.19)***	(-14.58)***	(-9.55)***	(-14.60)***	(-11.77)***	(-12.20)***	(-12.45)***
LnAge	-0.207	-0.262	-0.202	-0.245	-0.239	-0.237	-0.227	-0.284	-0.224	-0.266	-0.258	-0.260
	(-2.95)***	(-3.71)***	(-2.89)***	(-3.48)***	(-3.39)***	(-3.37)***	(-3.51)***	(-4.34)***	(-3.45)***	(-4.08)***	(-3.96)***	(-3.99)***
Secondary	0.005	0.006	0.006	0.008	0.004	0.003	0.007	0.008	0.008	0.010	0.006	0.005
	(1.45)	(2.00)**	(1.84)*	(2.38)**	(1.21)	(0.86)	(2.31)**	(2.80)***	(2.75)***	(3.30)***	(2.01)**	(1.73)*
VCDummy	0.412	0.507	0.440	0.532	0.370	0.342	0.229	0.318	0.257	0.350	0.185	0.170
	(3.16)***	(3.83)***	(3.39)***	(4.08)***	(2.79)***	(2.57)**	(1.90)*	(2.59)***	(2.14)**	(2.90)***	(1.51)	(1.38)
HiTechDummy	0.047	0.178	0.065	0.158	0.055	0.041	0.197	0.322	0.215	0.305	0.203	0.200
	(0.35)	(1.32)	(0.49)	(1.18)	(0.41)	(0.30)	(1.60)	(2.58)***	(1.74)*	(2.46)**	(1.63)	(1.60)
OIBD/AssetsAdj	0.025	-0.001	0.025	0.008	0.014	0.020	0.071	0.047	0.071	0.055	0.061	0.065
	(0.80)	(0.02)	(0.80)	(0.26)	(0.46)	(0.63)	(2.47)**	(1.60)	(2.47)**	(1.90)*	(2.11)**	(2.23)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1561	0.1357	0.1569	0.1443	0.1447	0.1464	0.1935	0.1707	0.1945	0.1808	0.1807	0.1810
N	5,342	5,342	5,342	5,342	5,342	5,342	5,302	5,302	5,302	5,302	5,302	5,302

Table 6. Relationship between lead IPO underwriter centrality and financial analyst following

The sample consists of IPOs conducted in 1980-2009. Degree, Indegree, Outdegree, Betweenness, Eigenvector, and 2-StepReach are measures of lead IPO underwriter centrality as described in section 5. NumAn is the number of analysts following the firm at the end of the fiscal year of IPO. MktShare is the lead underwriter's share of total proceeds raised in the IPO market in the previous five years. xMktShare is the residuals from a regression of MktShare on six lead IPO underwriter centrality measures. LnOffer is the natural logarithm of the IPO issue offer size. xLnOffer is the residuals from a regression of LnOffer on six lead IPO underwriter centrality measures. LnAssets is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. LnAge is the natural logarithm of one plus the number of years from IPO firm founding year to the IPO issue year. Secondary is the percentage of secondary shares offered in the IPO. 1/OfferPrice is the reciprocal of IPO offer price. VCDummy is a dummy equal to one for VC-backed IPOs. HiTechDummy is a dummy equal to one for Hi-Tech IPOs. Underpricing is the percentage difference between the first trading day closing price and IPO offer price. QFTDAdj is the industry-adjusted Tobin's Q ratio calculated as the ratio of the market value of assets to the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the first trading day closing price. The number of shares outstanding is as of the first trading day. The number of shares outstanding and the share price for industry peers is taken from the first available post-IPO quarter on Compustat. The book value of assets and the book value of equity both for IPO firms and industry peers are taken from the first available post-IPO quarter on Compustat. Industry adjustment is performed by subtracting the contemporaneous median Tobin's Q of IPO firm's 2-digit SIC code industry peers. All regressions are Poisson maximum likelihood estimations. All regressions include year and 2-digit SIC industry code dummies. *z*-statistics are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	NumAn	NumAn	NumAn	NumAn	NumAn	NumAn
Intercept	-0.398	-0.867	-0.395	-0.645	-0.321	-0.436
	(-0.57)	(-1.24)	(-0.57)	(-0.92)	(-0.46)	(-0.63)
Degree	1.103					
	(9.41)***					
Indegree		1.596				
		(3.82)***				
Outdegree			1.022			
			(9.22)***			
Betweenness				1.577		
				(6.50)***		
Eigenvector					1.790	
					(10.86)***	
2-Stepreach						0.728
						(11.77)***
xMktShare	0.816	1.089	0.830	0.969	0.992	0.948
	(2.73)***	(3.60)***	(2.78)***	(3.22)***	(3.32)***	(3.14)***
xLnOffer	0.118	0.047	0.109	0.060	0.127	0.183
	(7.41)***	(3.38)***	(7.08)***	(4.42)***	(8.17)***	(10.06)***
LnAssets	0.094	0.129	0.095	0.114	0.094	0.087
	(10.39)***	(15.80)***	(10.47)***	(13.28)***	(10.66)***	(9.79)***
LnAge	-0.027	-0.032	-0.027	-0.031	-0.028	-0.027
	(-2.34)**	(-2.78)***	(-2.30)**	(-2.65)***	(-2.45)**	(-2.31)**
Secondary	0.000	0.000	0.000	0.000	0.000	-0.000
	(0.45)	(0.22)	(0.55)	(0.82)	(0.24)	(-0.27)
1/OfferPrice	-2.670	-3.676	-2.780	-3.449	-2.297	-1.682
	(-6.83)***	(-9.70)***	(-7.17)***	(-9.16)***	(-5.78)***	(-4.06)***
VCDummy	0.136	0.134	0.135	0.139	0.125	0.133
	(6.26)***	(6.15)***	(6.22)***	(6.40)***	(5.74)***	(6.11)***
HiTechDummy	0.119	0.130	0.121	0.128	0.112	0.113
	(4.20)***	(4.58)***	(4.25)***	(4.50)***	(3.94)***	(3.98)***
Underpricing	0.001	0.001	0.001	0.001	0.001	0.001
	(2.82)***	(2.94)***	(2.76)***	(2.79)***	(3.12)***	(3.32)***
QFTDAdj	0.005	0.006	0.005	0.005	0.005	0.005
	(2.41)**	(3.08)***	(2.43)**	(2.80)***	(2.51)**	(2.51)**
OIBD/AssetsAdj	0.002	-0.001	0.002	-0.000	0.002	0.003
	(0.27)	(-0.25)	(0.26)	(-0.07)	(0.35)	(0.52)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.1109	0.1063	0.1107	0.1080	0.1127	0.1142
N	4,018	4,018	4,018	4,018	4,018	4,018

Table 7. Relationship between lead IPO underwriter centrality and the participation of institutional investors

The sample consists of IPOs conducted in 1980-2009. Degree, Indegree, Outdegree, Betweenness, Eigenvector, and 2-StepReach are measures of lead IPO underwriter centrality as described in section 5. InstN is the number of institutional investors holding IPO firm shares at the end of the first calendar quarter after IPO. InstP is the proportion of IPO firm shares held by institutional investors at the end of the first calendar quarter after IPO. xMktShare is the residuals from a regression of MktShare on six lead IPO underwriter centrality measures. LnOffer is the natural logarithm of the IPO issue offer size. xLnOffer is the residuals from a regression of LnOffer on six lead IPO underwriter centrality measures. LnAssets is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. LnAge is the natural logarithm of one plus the number of years from IPO firm founding year to the IPO issue year. Secondary is the percentage of secondary shares offered in the IPO. 1/OfferPrice is the reciprocal of IPO offer price. VCDummy is a dummy equal to one for VC-backed IPOs. HiTechDummy is a dummy equal to one for Hi-Tech IPOs. Underpricing is the percentage difference between the first trading day closing price and IPO offer price. QFTDAdj is the industry-adjusted Tobin's Q ratio calculated as the ratio of the market value of assets to the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the first trading day closing price. Regressions (1) through (6) are negative binomial maximum-likelihood estimations and regressions (7) through (12) are OLS estimations. All regressions include year and 2-digit SIC industry code dummies. *z*-statistics are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Dependent	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
variable	InstN	InstN	InstN	InstN	InstN	InstN	InstP	InstP	InstP	InstP	InstP	InstP
Intercept	0.568	-0.327	0.513	-0.156	0.358	0.761	-0.042	-0.158	-0.066	-0.190	-0.075	0.073
	(1.75)*	(-0.98)	(1.57)	(-0.47)	(1.11)	(2.42)**	(-0.44)	(-1.69)*	(-0.70)	(-2.02)**	(-0.80)	(0.78)
Degree	2.388						0.311					
	(28.31)***						(11.50)***					
Indegree		5.812						0.867				
		(19.45)***						(9.72)***				
Outdegree			2.111						0.274			
			(26.33)***						(10.45)***			
Betweenness				2.895						0.358		
				(15.43)***						(5.96)***		
Eigenvector					3.114						0.334	
					(30.25)***						(11.26)***	
2-Stepreach						1.591						0.182
						(41.54)***						(17.01)***
xMktShare	0.207	0.281	0.245	0.256	0.540	0.223	-0.168	-0.142	-0.163	-0.135	-0.121	-0.174
	(0.88)	(27.43)***	(1.04)	(25.28)***	(2.35)**	(1.04)	(-1.98)**	(-1.68)*	(-1.92)*	(-1.58)	(-1.43)	(-2.10)**
xLnOffer	0.381	0.523	0.354	0.480	0.370	0.547	0.051	0.042	0.048	0.037	0.046	0.067
	(34.21)***	(2.19)**	(32.59)***	(1.98)**	(34.81)***	(44.93)***	(15.01)***	(13.42)***	(14.33)***	(11.81)***	(14.36)***	(18.76)***
LnAssets	0.071	0.130	0.076	0.118	0.079	0.042	0.011	0.018	0.013	0.019	0.013	0.004
	(11.67)***	(22.58)***	(12.53)***	(19.55)***	(13.42)***	(7.21)***	(5.48)***	(10.09)***	(6.29)***	(10.32)***	(6.57)***	(2.01)**
LnAge	-0.005	-0.019	-0.005	-0.014	-0.010	-0.005	0.012	0.011	0.012	0.011	0.012	0.012
	(-0.70)	(-2.35)**	(-0.67)	(-1.66)*	(-1.25)	(-0.74)	(4.74)***	(4.08)***	(4.73)***	(4.27)***	(4.49)***	(4.70)***
Secondary	0.002	0.001	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.000
	(5.60)***	(4.06)***	(6.03)***	(6.35)***	(4.74)***	(3.07)***	(5.85)***	(5.25)***	(6.23)***	(6.67)***	(5.29)***	(3.97)***
1/OfferPrice	-5.211	-6.105	-5.598	-6.621	-4.647	-2.465	-0.012	-0.013	-0.014	-0.019	-0.009	0.004
	(-22.46)***	(-25.63)***	(-24.33)***	(-28.34)***	(-19.56)***	(-10.25)***	(-1.04)	(-1.17)	(-1.26)	(-1.67)*	(-0.82)	(0.32)
VCDummy	0.168	0.160	0.169	0.179	0.139	0.142	0.027	0.026	0.028	0.030	0.023	0.019
	(11.60)***	(10.56)***	(11.57)***	(11.76)***	(9.62)***	(10.32)***	(5.64)***	(5.34)***	(5.84)***	(6.32)***	(4.79)***	(4.09)***
HiTechDummy	0.038	0.040	0.044	0.058	0.013	0.009	-0.018	-0.018	-0.017	-0.015	-0.021	-0.023
	(2.00)**	(2.00)**	(2.31)**	(2.94)***	(0.70)	(0.51)	(-2.86)***	(-2.86)***	(-2.67)***	(-2.31)**	(-3.34)***	(-3.78)***
Underpricing	0.003	0.003	0.003	0.003	0.003	0.003	0.000	0.000	0.000	0.000	0.000	0.000
	(15.00)***	(15.52)***	(14.71)***	(14.58)***	(16.23)***	(17.33)***	(3.16)***	(3.81)***	(3.17)***	(3.60)***	(3.58)***	(3.19)***
QFTDAdj	-0.002	0.003	-0.001	0.001	-0.001	-0.001	-0.005	-0.005	-0.005	-0.005	-0.005	-0.006
	(-0.89)	(1.45)	(-0.77)	(0.48)	(-0.32)	(-0.56)	(-8.23)***	(-7.29)***	(-8.09)***	(-7.38)***	(-7.97)***	(-8.55)***
OIBD/AssetsAdj	0.004	-0.002	0.003	-0.001	0.003	0.008	0.000	-0.000	0.000	-0.000	0.000	0.001
	(1.01)	(-0.43)	(0.87)	(-0.32)	(0.98)	(2.18)**	(0.43)	(-0.06)	(0.33)	(-0.20)	(0.35)	(1.03)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.1662	0.1563	0.1636	0.1529	0.1689	0.1872	0.3344	0.3292	0.3312	0.3210	0.3336	0.3549
N	4,900	4,900	4,900	4,900	4,900	4,900	4,900	4,900	4,900	4,900	4,900	4,900

Table 8. Relationship between lead IPO underwriter centrality and post-IPO stock return performance

The sample consists of IPOs conducted in 1980-2009. Degree, Indegree, Outdegree, Betweenness, Eigenvector, and 2-StepReach are measures of lead IPO underwriter centrality as described in section 5. 1YearHPRAdj is the IPO firms' one-year holding period return calculated by compounding daily returns over 252 trading days after the IPO (excluding the first trading day's return) adjusted for (minus) the holding period return of the NASDAQ value-weighted index over the same period. If an IPO firm is delisted before the end of the one-year period, returns of the IPO firm and NASDAQ value-weighted index are compounded until the delisting date. MktShare is the lead underwriter's share of total proceeds raised in the IPO market in the previous five years. xMktShare is the residuals from a regression of MktShare on six lead IPO underwriter centrality measures. LnOffer is the natural logarithm of the IPO issue offer size. xLnOffer is the residuals from a regression of LnOffer on six lead IPO underwriter centrality measures. LnAssets is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. LnAge is the natural logarithm of one plus the number of years from IPO firm founding year to the IPO issue year. VCDummy is a dummy equal to one for VC-backed IPOs. HiTechDummy is a dummy equal to one for Hi-Tech IPOs. Underpricing is the percentage difference between the first trading day closing price and IPO offer price. QFTDAdj is the industry-adjusted Tobin's Q ratio calculated as the ratio of the market value of assets to the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of common equity plus the number of shares outstanding times the first trading day closing price. The number of shares outstanding is as of the first trading day. The number of shares outstanding and the share price for industry peers is taken from the first available post-IPO quarter on Compustat. The book value of assets and the book value of equity both for IPO firms and industry peers are taken from the first available post-IPO quarter on Compustat. Industry adjustment is performed by subtracting the contemporaneous median Tobin's Q of IPO firm's 2-digit SIC code industry peers. OIBD/AssetsAdj is the operating income before depreciation over the book value of assets at the end of the fiscal year prior to IPO adjusted for the contemporaneous median OIBD/Assets of 2-digit SIC code industry peers. All regressions include year dummies. *t*-statistics are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	1YearHPRAdj	1YearHPRAdj	1YearHPRAdj	1YearHPRAdj	1YearHPRAdj	1YearHPRAdj
Intercept	-0.514	-0.608	-0.530	-0.641	-0.604	-0.607
	(-1.90)*	(-2.32)**	(-1.96)**	(-2.44)**	(-2.25)**	(-2.21)**
Degree	0.371					
	(2.60)***					
Indegree		1.177				
		(2.53)**				
Outdegree			0.352			
			(2.52)**			
Betweenness				0.589		
				(1.82)*		
Eigenvector					0.269	
					(1.77)*	
2-Stepreach						0.075
						(1.41)
xMktShare	0.083	0.101	0.084	0.115	0.131	0.102
	(0.17)	(0.21)	(0.18)	(0.24)	(0.28)	(0.22)
xLnOffer	-0.042	-0.050	-0.044	-0.055	-0.054	-0.051
	(-2.41)**	(-3.09)***	(-2.53)**	(-3.40)***	(-3.26)***	(-2.83)***
LnAssets	0.043	0.049	0.044	0.051	0.049	0.049
	(4.45)***	(5.64)***	(4.63)***	(5.72)***	(5.16)***	(4.91)***
LnAge	-0.001	-0.003	-0.001	-0.002	-0.002	-0.003
	(-0.07)	(-0.25)	(-0.05)	(-0.15)	(-0.18)	(-0.20)
VCDummy	0.002	-0.001	0.003	0.006	-0.000	0.001
	(0.06)	(-0.05)	(0.12)	(0.25)	(-0.01)	(0.04)
HiTechDummy	0.095	0.095	0.096	0.099	0.095	0.096
	(3.67)***	(3.66)***	(3.71)***	(3.83)***	(3.65)***	(3.70)***
Underpricing	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.02)	(-0.84)	(-1.04)	(-0.94)	(-0.91)	(-0.90)
QFTDAdj	0.004	0.004	0.004	0.004	0.004	0.004
	(1.20)	(1.37)	(1.21)	(1.35)	(1.33)	(1.36)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0298	0.0298	0.0298	0.0292	0.0292	0.0290
N	5,642	5,642	5,642	5,642	5,642	5,642

Table 9. Instrumental variable two-stage least squares regression analysis of the effect of lead IPO underwriter centrality on IPOs

The sample consists of IPOs conducted in 1980-2009. In first stage regressions instrumental variable GS takes values 0, 1, and 2 for IPO firms which went public in 1980-1999, 2000-2004, and 2005-2009, respectively. In second stage regressions DegreeHat is the predicted value of Degree from the first stage regressions. Degree is a measure of lead IPO underwriter centrality as described in section 5. Underpricing is the percentage difference between the first trading day closing price and IPO offer price. MktShare is the lead underwriter's share of total proceeds raised in the IPO market in the previous five years. xMktShare is the residuals from a regression of MktShare on six lead IPO underwriter centrality measures. LnOffer is the natural logarithm of the IPO issue offer size. xLnOffer is the residuals from a regression of LnOffer on six lead IPO underwriter centrality measures. LnAssets is the natural logarithm of the book value of total assets at the end of the fiscal year prior to the IPO. LnAge is the natural logarithm of one plus the number of years from IPO firm founding year to the IPO issue year. Secondary is the percentage of secondary shares offered in the IPO. 1/OfferPrice is the reciprocal of IPO offer price. VCDummy is a dummy equal to one for VC-backed IPOs. HiTechDummy is a dummy equal to one for Hi-Tech IPOs. OIBD/AssetsAdj is the operating income before depreciation over the book value of assets at the end of the fiscal year prior to IPO adjusted for the contemporaneous median OIBD/Assets of 2-digit SIC code industry peers. *t*-statistics of first stage regressions and *z*-statistics of second stage regressions are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Panel A: The effect of lead IPO underwriter centrality on offer price revision, IPO and secondary market valuation, and IPO initial return

AbsRevision is the absolute percentage difference between the IPO offer price and the midpoint of original filing range. QOPAdj and QFTDAdj are the industry-adjusted Tobin's Q ratios calculated using IPO offer price and first trading day price, respectively. PriorMktReturn is the return on the CRSP value-weighted index over the 30-day period prior to the IPO. AbsMktReturn is the absolute return on the CRSP value-weighted index between the filing date and the IPO issue date. FilingWidth is the percentage difference between the original high filing price and original low filing price.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	First stage regression	Second stage regression	First stage regression	Second stage regression	First stage regression	Second stage regression	First stage regression	Second stage regression
	Degree	AbsRevision	Degree	QOPAdj	Degree	Underpricing	Degree	QFTDAdj
Intercept	-0.534	0.924	-0.623	11.968	-0.446	-92.904	-0.623	15.003
	(-15.35)***	(1.78)*	(-45.41)***	(11.06)***	(-13.00)***	(-1.24)	(-45.41)***	(8.65)***
GS	0.016		0.048		0.02		0.048	
	(2.57)***		(22.25)***		(3.34)***		(22.25)***	
DegreeHat		1.954		6.393		-250.507		8.524
		(2.03)**		(4.54)***		(-1.52)		(3.77)***
xMktShare	-0.206	0.513	0.088	3.638	-0.197	-7.545	0.088	1.042
	(-3.42)***	(2.02)**	(1.82)*	(6.97)***	(-3.40)***	(-0.30)	(1.82)*	(7.09)***
xLnOffer	-0.040	0.078	-0.055	0.638	-0.047	14.049	-0.055	12.889
	(-23.75)***	(2.06)**	(-35.25)***	(2.41)**	(-28.53)***	(0.97)	(-35.25)***	(5.32)***
LnAssets	0.034	-0.059	0.043	-0.687	0.027	5.506	0.043	-0.832
	(39.12)***	(-1.83)*	(50.28)***	(-9.47)***	(29.86)***	(1.24)	(50.28)***	(-7.15)***
LnAge	-0.005	0.002	-0.009	-0.064	-0.006	-4.205	-0.009	-0.276
	(-3.89)***	(0.26)	(-6.17)***	(-1.41)	(-4.24)***	(-3.54)***	(-6.17)***	(-3.78)***
Secondary			0.000	0.005	0.000	-0.146	0.000	-0.002
			0.68	(2.78)***	-0.72	(-3.90)***	0.68	(-0.52)
1/OfferPrice					-0.003	2.700		
					(-2.18)**	(3.16)***		
VCDummy	0.028	-0.011	0.024	0.140	0.022	7.951	0.024	0.590
	(10.28)***	(-0.41)	(9.25)***	(1.57)	(8.37)***	(2.05)**	(9.25)***	(4.13)***
HiTechDummy	0.021	-0.012	0.034	-0.080	0.017	6.571	0.034	0.365
	(6.08)***	(-0.54)	(12.93)***	(-0.79)	(5.04)***	(1.93)*	(12.93)***	(2.27)**
AbsRevision					0.068	79.191		
					(9.11)***	(6.52)***		
PriorMktReturn					0.043	99.845		
					1.31	(5.25)***		
AbsMktRet	0.032	0.212						
	(1.38)	(3.18)***						
FilingWidth	-0.008	0.376						
	(-0.69)	(12.53)***						
OIBD/AssetsAdj			-0.005	0.002			-0.005	0.008
			(-7.36)***	(0.08)			(-7.36)***	(0.23)
Ind. Dummies	Yes	Yes	No	No	Yes	Yes	No	No
Exch. Dummies	No	No	No	No	Yes	Yes	No	No
Centered R^2	0.3504	-0.5389	0.4704	0.0912	0.4103	-0.2472	0.4704	0.1175
N	4,493	4,493	5,342	5,342	4,472	4,472	5,342	5,342
F-statistic	6.60		495.18		11.16		495.18	
(*p*-value)	(0.010)		(0.000)		(0.000)		(0.000)	

Table 9 (continued)

Panel B: The effect of lead IPO underwriter network centrality on the number of analysts following IPO firm, the number of institutional investors holding IPO firm shares, and post-IPO stock return performance

LnNumAn is the natural logarithm of the number of analysts following the firm at the end of the fiscal year of IPO. LnInstN is the natural logarithm of the number of institutional investors holding IPO firm shares at the end of the first calendar quarter after IPO. 1YearHPRAdj is the IPO firms' one-year holding period return calculated by compounding daily returns over 252 trading days after the IPO (excluding the first trading day's return) adjusted for (minus) the holding period return of the NASDAQ value-weighted index over the same period. If an IPO firm is delisted before the end of the one-year period, returns of the IPO firm and NASDAQ value-weighted index are compounded until the delisting date.

	(1)	(2)	(3)	(4)	(5)	(6)
	First stage regression	Second stage regression	First stage regression	Second stage regression	First stage regression	Second stage regression
Dependent variable	Degree	LnNumAn	Degree	LnInstN	Degree	1YearHPRAdj
Intercept	-0.404	-0.304	-0.691	-0.379	-0.591	-0.898
	(-6.94)***	(-0.74)	(-16.01)***	(-0.87)	(-47.16)***	(-2.94)***
GS	0.049		0.045		0.050	
	(22.71)***		(21.06)***		(24.18)***	
DegreeHat		2.788		4.682		0.162
		(9.68)***		(12.99)***		(0.39)
xMktShare	0.086	0.219	0.037	0.568	-0.007	0.327
	(1.82)*	(0.88)	(0.79)	(0.16)	(-0.16)	(0.69)
xLnOffer	-0.080	0.270	439204	-0.057	-0.054	-0.059
	(-47.97)***	(8.61)***	(-40.63)***	(-21.89)***	(-36.34)***	(-2.20)**
LnAssets	0.033	0.038	0.043	0.114	0.040	0.047
	(30.35)***	(2.78)***	(46.00)***	(6.05)***	(51.45)***	(2.31)**
LnAge	-0.005	-0.002	-0.005	0.012	-0.006	0.002
	(-3.34)***	(-0.21)	(-3.67)***	(1.08)	(-4.75)***	(0.18)
Secondary	-0.000	0.000	0.000	0.002		
	(-3.29)***	(0.82)	(0.48)	(4.02)***		
1/OfferPrice	-1.078	-0.604	-0.040	-0.241		
	(-25.43)***	(-1.51)	(-6.29)***	(-4.78)***		
VCDummy	0.000	0.133	0.014	0.283	0.020	0.004
	(0.13)	(7.13)***	(5.10)***	(13.57)***	(7.86)***	(0.13)
HiTechDummy	0.018	0.081	0.022	0.091	0.027	0.072
	(4.67)***	(3.16)***	(6.27)***	(3.25)***	(10.72)***	(2.49)**
Underpricing	0.000	0.001	0.000	0.003	0.000	-0.001
	(4.07)***	(2.44)**	(8.83)***	(12.22)***	(10.90)***	(-2.09)**
QFTDAdj	0.002	0.004	0.003	-0.003	0.002	0.004
	(5.96)***	(1.79)*	(8.51)***	(-0.90)	(8.12)***	(1.20)
OIBD/AssetsAdj	-0.003	0.007	-0.004	0.001		
	(-5.40)***	(1.76)*	(-6.71)***	(0.14)		
Ind. Dummies	Yes	Yes	Yes	Yes	No	No
Centered R^2	0.5665	0.3119	0.5165	0.6551	0.4848	0.0128
N	4,018	4,018	4,900	4,900	5,642	5,642
F-statistic	515.72		443.60		584.53	
(*p*-value)	(0.000)		(0.000)		(0.000)	