University of Arkansas, Fayetteville

ScholarWorks@UARK

Graduate Theses and Dissertations

8-2018

Essays in Networks of Finance and Experimental Finance: A Behavioral View

Weineng Xu
University of Arkansas, Fayetteville

Follow this and additional works at: https://scholarworks.uark.edu/etd

Part of the Finance Commons

Citation

Xu, W. (2018). Essays in Networks of Finance and Experimental Finance: A Behavioral View. *Graduate Theses and Dissertations* Retrieved from https://scholarworks.uark.edu/etd/2929

This Dissertation is brought to you for free and open access by ScholarWorks@UARK. It has been accepted for inclusion in Graduate Theses and Dissertations by an authorized administrator of ScholarWorks@UARK. For more information, please contact scholar@uark.edu, uarepos@uark.edu.

Essays in Networks of Finance and Experimental Finance: A Behavioral View

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy in Business Administration with a concentration in Finance

by

Weineng Xu
East China Normal University
Bachelor of Economics, 2011
University of Cincinnati
Master of Arts in Applied Economics, 2013

August 2018
University of Arkansas

This dissertation is approved for recommendation to the Graduate Council.

Tomas Jandik, Ph.D.
Dissertation Director

Scott Hsu, Ph.D.
Committee Member

Timothy J. Yeager, Ph.D.
Committee Member

Abstract

Behavioral and managerial biases can occur among corporate executives that lead to suboptimal decision making and outcomes for the shareholders. In the first essay, I study how the personal networks of CEO affect the performance of the firm in the context of IPO. I find that CEOs at higher social hierarchical positions can allow managerial entrenchment and prevent dismissal. The findings show that influential CEOs are associated with higher IPO underpricing, lower likelihood of positive offer price revision, and lower likelihood of wealth creation for the pre-IPO shareholders. In the second essay, I explore how the social connections between bidder and bidder advisors affect M&A outcomes. I show that the M&A deals with a bidder-bidder financial advisor connection exists have a lower CAR at announcement than the deals without such connections. I also show that M&A deals advised by personally connected financial advisor are more likely to complete but are executed less efficiently in terms of time to resolution. I find evidence that both the bidder CEO and the financial advisor receive higher cash bonus and advisor fees, respectively, when there are bidder-bidder financial advisor connections exist. Behavioral bias can also occur among individuals and lead to asset bubbles, especially in an environment with widely available credit and increased wealth inequality. In the third essay, using an experimental approach, I study how wealth inequality, leverage, and the effect that people trying to keep up with the status benchmark, which is so called "Joneses effect", affect the asset bubbles. I find that unequal initial endowments and the presence of a Joneses effect lead to substantial overpricing as compared to situations where only unequal initial endowment or both factors are absent.

©2018 by Weineng Xu
All Rights Reserved

Acknowledgement

The research in Chapter 1 is supported in part by the National Science Foundation through grants MRI #0722625 (Star of Arkansas), MRI-R2 #0959124 (Razor), ARI #0963249, #0918970 (CI-TRAIN), and a grant from the Arkansas Science and Technology Authority, with resources managed by the Arkansas High Performance Computing Center.

For the research in Chapter 3, we appreciate the generous financial support from the Bank of America Research Fund Honoring James H. Penick and the Arkansas Bankers Association Endowed Chair.

Table of Contents

Chapter 1

CEO Network Centrality and IPO Performance

1. Introduction

The purpose of this paper is to examine the link between the outcomes of Initial Public Offerings (IPOs) and the personal social network of the Chief Executive Officer (CEO) leading the firm at the time of the IPO. We build on fast growing literature that deals with the importance of social ties – such as shared past employment, shared educational overlaps or joint top positions in social clubs – in finance. So far, financial research has documented both benefits and costs of such connections. Personal ties facilitate transfer of information among corporate decision makers, which leads to more efficient loan contracting (Engelberg, Gao, and Parsons, 2012), better analyst performance (Cohen, Malloy, and Frazzini, 2010), improved portfolio manager performance (Cohen, Frazzini, and Malloy, 2008), greater M&A synergies (Cai and Sevilir, 2012), and overall better corporate performance (Fracassi, 2014). On the other hand, inter-personal connections have been found to interfere with optimal corporate governance and monitoring of managers (Fracassi and Tate, 2012), to increase transaction costs (Cai, Walkling, and Yang, 2015), as well as to lead to collusion among contracting managers at the expense of investors (Ishii and Xuan, 2014).

In the context of IPOs, finance studies so far have documented large benefits due to social ties. Cooney, Madureira, Singh, and Yang (2015) find that investment banks are more likely to be included in the IPO underwriting syndicate, and are more likely to serve in a leading role within the syndicate, if bankers have bilateral social links to the IPO firm managers. The linked investment banks also receive higher compensation and larger IPO share allocation. At the same time, though, linked underwriters are also able to generate greater wealth gains for the pre-IPO shareholders (the gains on the shares those investors retain significantly exceed losses due to underpricing). Chuluun (2015) shows that IPOs underwritten by investment banks that occupy more central positions in the overall bank network, as well as banks that work with partners with previous industry experience, are associated with higher likelihood of large positive IPO subscription price revisions, as well as with higher short-run IPO stock returns.

Our paper builds on the previous IPO-related research, but unlike the effect of bilateral social links (Cooney et al., 2015), our focus is on the overall position of CEOs within the full network of all business decision makers - officers and directors of both public and private firms worldwide. Our approach allows us to capture the concept of social hierarchy. Bilateral ties often do not have an equal impact on the connected parties. People who are in higher social hierarchical positions have superior opportunities to transmit, gather, and control information, making such individuals more influential and powerful (e.g. Mizruchi and Potts 1998). We follow graph theory studies (Proctor and Loomis, 1951; Sabidussi, 1966; Freeman, 1977; Bonacich, 1972) that establish that social network centrality – a set of measures that characterizes the overall position of an individual within a network – describes the personal ability to influence information flows as well as contractual outcomes (e.g. Padgett and Ansell, 1993; Jackson, 2010). In contrast to previous studies based on bilateral ties, we are able to capture the ability of the CEO to affect information flows that pass through the entire network, and influence others even if no prior link exist. We focus on two centrality measures commonly utilized in social network research: degree centrality (the number of direct links between the CEO and any other members of the network) that assesses the personal network size, as well as eigenvector centrality that evaluates the relevance of the personal network (by giving greater weight to well-connected individuals linked to the CEO). Both of these measures have been associated with greater individual influence and power (e.g. Mizruchi and Potts 1998). Consequently, we utilize the measures of CEO influence and power to analyze the IPO outcomes to answer the following questions: Are IPOs lead by well-connected CEOs associated with greater or lower underpricing? Do underwriters of IPOs with central CEOs tend to adjust subscription prices prior to the IPO launch date? And, ultimately, do initial pre-IPO owners gain or lose during IPOs managed by central CEOs?

Our emphasis on the centrality within individual networks (based on nearly 800,000 business executives and board members of worldwide public and private firms, tracked by BoardEx database) is also conceptually different from studies that examine the effects of overall firm connectedness – that is, a position of a firm in the overall network of companies, typically based on board overlaps. The key difference is that more central firms should unambiguously generate benefits for the investors from the positions of higher influence and power. Larcker, So, and Wang (2013) show that high-centrality firms have superior accounting performance, Chuluun, Prevost, and Puthenpurackal (2014) link high firm centrality to lower loan costs and overall improved debt contracting, and Chuluun (2015) finds that more central underwriters are associated with more valuable IPO outcomes. However, individual managers may utilize their higher influence and power derived from more central network positions both for firm and personal benefits. Fogel, Jandik, and McCumber (2015) show that high-centrality CFOs tend to negotiate debt contracts that benefits their firms in the form of lower loan spreads and less restrictive covenant structures. On the other hand, El-Khatib, Fogel, and Jandik (2015) document that high-centrality CEOs of acquiring firms tend to launch M&A deals that benefit CEOs (in terms of higher pecuniary and non-pecuniary benefits), but generate losses to the bidder shareholders. El-Khatib et al. (2015) further find that high-centrality status enables CEOs to increase entrenchment, and mitigate both internal and external monitoring and disciplining of their activities. Consequently, the ultimate impact of CEO centrality on IPO outcomes examined in our study is an empirical issue.[1]

There are several reasons CEO centrality should affect IPO outcomes. Financial literature (e.g. Chava and Purnanandam, 2009; Graham, Harvey, and Puri, 2013) has documented that CEOs are the main firm decision makers whose actions have the greatest impact on firm performance. The CEOs of IPO firms should have even greater influence on their firms, because IPO companies tend to be relatively young and small. IPO research ever since Rock (1986) has shown that information asymmetry between IPO insiders and outside shareholders is positively associated with the magnitude of IPO underpricing (i.e. the stock return on the IPO first trading day). High information asymmetry makes investments by outsiders riskier, creating the need for higher underpricing in order to induce outside investor participation in the IPO. Since greater network influence should allow CEOs superior access to information and better ability to communicate information (Burt, 2011; Jackson, 2010; Newman, 2010), CEO centrality can reduce the

[1] Another difference between previous research on firm centrality and our focus on individual networks is the computational complexity. Firm networks typically contain at most several thousands of nodes, and thus firm centralities can be computed relatively quickly. On the other hand, individual networks involve hundreds of thousands of nodes connected by many millions of links, making centrality computation very high computer memory-intensive. For example, eigenvector centrality calculations for the network on links that exist in 2012 takes more than three days to converge.

information asymmetry between insiders and outside investors. High-centrality CEOs may also be considered more trustworthy information sources, as networks facilitate information filtering, screening and monitoring (Burt 1997, 2005, 2011; Nahapiet and Ghosal, 1998). Next, network centrality may facilitate reputation effects via voluntary bonding of highly central individuals, because networks allow easier sanctioning of negative behavior and creating social liabilities (Boot et al., 1993; Burt, 2005; Brass and Labianca, 2006). All of the above arguments imply that IPOs lead by well-connected CEOs should be less risky due to a lower degree of information asymmetry, and as such associated with smaller underpricing. On the other hand, high-centrality managers may be isolated from monitoring and market discipline, allowing them to pursue activities that enrich managers at the expense of shareholders. El-Khatib et al. (2015) find that highly central bidder CEOs are less likely to be fired after value-destroying acquisitions, and that they use their superior access to information to benefit from insider trades – especially inside selling.[2] These results suggest that well-connected CEOs may have tendencies to get engaged in self-serving activities at the expense of shareholders. If high-centrality CEOs of IPO companies have similar incentives, then new shareholders may perceive such IPOs as risky and demand higher compensation in the form of greater underpricing for their willingness to invest.

While IPO research traditionally associates greater underpricing with risky IPOs subject to large information asymmetry, some papers (e.g., Krigman, Shaw, and Womack, 2001) consider higher underpricing a sign of IPO success due to effective marketing effort of underwriters.[3] Consequently, we analyze additional IPO factors in order to provide truly unambiguous tests regarding the benefits and costs of having a well-connected CEO at the time of an IPO. First, we study the determinants of the likelihood of offer price increase from the initial filing range. Second, and more importantly, we analyze the total net gain to pre-IPO owners due to the IPO process. We follow Cook, Kieschnick, and Van Ness (2006) and

[2] El-Khatib et al. (2015) document that a change from 25th to 75th sample percentile bidder CEO centrality is associated with a 7.24 percentage point reduction in three-month returns following inside sell orders throughout CEO careers. The overall mean and median career post-selling returns are negative for high-centrality CEOs.

[3] On the other hand, IPO companies suffer monetary losses due to underpricing, and Dunbar (2000) shows that underwriters that underprice their IPOs tend to subsequently lose market share.

define the net IPO gain as the difference between IPO "wealth effect" (difference between the closing first trading day price and the midpoint of the IPO's initial filing range for the portion of shares pre-IPO owners retain) and IPO "dilution effect" (the difference between the closing first trading day price and the offer price for the portion of IPO shares sold). If high-centrality CEOs generate primarily benefits for the pre-IPO owners, then the likelihood of positive IPO net gain should be an increasing function of CEO centrality.

Our worldwide network of executives and directors of public and private companies is constructed utilizing BoardEx database. BoardEx tracks interpersonal links created through past work relationships, joint educational overlaps, and memberships in social clubs, charities, etc. We compute individual degree and eigenvector centralities based on annual networks created from past employment in public and private companies worldwide. Such links are typically reliably verifiable, not subject to self-reporting bias, and most likely describe relationships where two linked individuals indeed met each other (unlike educational links based on attending the same educational institution, often with dozens of thousands of students).[4] We assume that once established, links between two parties exist until one participant dies. As a result, our social networks grow in size over time. In the last sample year, 2013, our worldwide network contains nearly 41 million employment links formed by almost 560,000 firm executives and directors.

Based on a sample of 906 IPOs between 2001 and 2013, we find that high-centrality CEOs are associated with higher underpricing. A firm whose CEO is in the 90th sample percentile of eigenvector centrality has the initial underpricing return higher by 9.29 percentage points compared to a firm whose CEO is in the 10th sample centrality percentile. This is a significant change compared to the median 8.16% first-day return for the firms in our sample. At the same time, IPO firms with high centrality CEOs have a significantly lower likelihood of offer price increase from the initial filing range. Ultimately, we document that companies with well-connected CEOs have the lowest chance to generate positive IPO net wealth effects – that is, the value-reducing dilution effect on shares sold dominates wealth gains on shares retained for pre-IPO owners in these firms. All of our findings are consistent with the overall negative impact of

[4] In unreported robustness analysis, we create networks based on alternative definitions of links – such as educational and social overlaps. Our findings are similar to those presented in the main tables of this study.

CEO influence and power – as proxied by network centrality – in the context of IPO process.

We further show the high underpricing persists, and the likelihood of positive net wealth effects is low for IPOs with high centrality CEOs whose networks are "inefficient" – that is, large in size (high degree centrality), but devoid of influential nodes (low eigenvector centrality). Such networks are least likely to mitigate information costs and aid information transfer to investors.

Additionally, we document that one of the potential reasons for the problems associated with IPOs lead by high centrality CEOs is that the managerial labor market disciplining mechanisms are weak for those CEOs. While in general, low post-IPO long term performance is associated with higher likelihood of being replaced (a finding that is similar to Jenter and Kanaan, 2015), we find that the magnitude of post-IPO losses is unrelated to the turnover for high centrality CEOs. This finding suggests high network centrality allows CEOs to insulate themselves from monitoring of their activities and to achieve greater entrenchment.

Last, we find that CEOs with high centrality generate significantly lower post-sale abnormal returns for both two-month and three-month periods following their sale of company's stock. Consequently, IPO firms lead by high centrality CEOs may be perceived more risky because the CEOs with higher centrality tend to more often sell their shares before negative information gets revealed (thus benefitting themselves at the expense of the buyers), taking advantage of their insider information.

Our results hold under various robustness checks. Most importantly, CEO centrality effects are unaffected even after we control for past relationships between the IPO firm managers and the underwriters (Cooney et al., 2015). Also, our results are very similar to those presented in this study if we substitute CEO centrality with the "excess centrality" equal to the difference between actual centrality and its predicted level based on firm and personal determinants of centrality. Additionally, our results hold after we control for effects of CEO's age and years in the position.[5] Last, our results are unaffected by inclusion of CEO overconfidence measures, and by utilizing an instrumental variable approach. Based on our robustness checks, our results are more likely due to the CEO network "social" capital (that is, information and

[5] In unreported results, we find that being an older CEOs can reduce the impact of CEO centrality on IPO underpricing, but being a long tenured CEO does not have significant impact on IPO underpricing.

reputational effects that can be attained via social networks - e.g. Woolcock, 1998), and less likely due to CEOs "human" capital (that is, omitted variables related to skills and other personal attributes that may be correlated with CEO centrality).

Our study makes several notable contributions. First, we add to the growing research on the importance of social networks in financial contracting. We are the first paper to study the role of individual– as opposed to firm – position within the whole social network of all business decision makers in the context of IPOs. A more central place puts the CEO higher in the social network hierarchy, and enables the CEO to be more influential and powerful. Our findings suggest that new IPO investors recognize that higher influence and power allows the CEOs to achieve greater entrenchment and to diminish the effectiveness of monitoring of CEO activities. Consequently, new investors demand higher compensation in the form of greater underpricing for their willingness to invest, which causes substantial dilution effects on IPO shares sold, and leaves pre-IPO investors with a lower likelihood of positive net wealth effects as the consequence of the IPO. In this regard, our study provides a contrasting view on the role of networking in the IPO process to papers that found prevailing beneficial effects for bilateral connections between IPO and underwriter managers (Cooney et al., 2015) and for the underwriter firm-specific centralities (Chuluun, 2015).[6]

Second, we extend the literature on determinants of IPO underpricing and IPO overall wealth effects. We show that in addition to the known firm- and deal-specific determinants, the social network position of the CEO, related to influence and power, matter for IPO processes.

Third, we contribute to research on the role of personal traits in finance (e.g. Malmendier and Tate, 2008; Billett and Qian, 2008; Cronquist, Makhija, and Yonker, 2012; Otto, 2014). However, unlike many previous studies where the personal traits of managers are taken from surveys or questionnaires (e.g. Kaplan, Klebanov, Sorensen, 2012; Graham, Harvey, Puri, 2013), CEO influence and power studied in our

[6] We do not claim, however, that CEO centrality generates no benefits to investors. First, we find that underpricing is lower, and the likelihood of positive IPO net wealth effects for pre-IPO owners is higher in cases of IPOs with CEOs who have "efficient" networks (i.e., networks that are not characterized by the combination of high degree, but low eigenvector centrality). Second, high CEO network centrality may produce significant advantages for firm's day-to-day operations. The findings in this study suggest, though, that CEO network centrality may cause challenges within the actual IPO process – that is, the sale of IPO shares to new investors.

paper is based on quantifiable measures of network centrality, which utilizes objectively observable existence of social links. Importantly, the network centrality based on past work-related relationships is unlikely to be endogenous to the IPO outcomes we investigate. Network centrality is thus an ideal measure for studying the impact of managerial behavior on corporate outcomes, because it does not bring issues of potential reverse causality.

The paper proceeds as follows. Section 2 describes our data. Section 3 presents the results and robustness check. Section 4 concludes.

2. Data

2.1 CEO centrality

We construct our centrality measures using data available from BoardEx. This database contains information about bilateral connections, education background and employment history, as well demographical and tenure information of the board members and senior executives of the firms all over the world. BoardEx forms different networks based on geographical regions and the way that people in the networks overlap. The entire network contains individual from all geographical regions with overlaps in employment, education, and social activities. It covers 574,645 individuals with 60 million links in its maximum network in 2013. In our paper, we use centrality measures generated from individuals' overlap in employment worldwide because that is the most reliable connection type. Education and social activity connections are less reliable in that the sizes of the institutions (e.g., universities) where two overlapping people meet tend to be big and therefore the chances are slim that two overlapping people even actually interact during the years they both attend the institution. Our global network with employment overlapping results in a total of 559,490 individuals with 41 million bilateral connections.

Centrality measures how powerful an individual is in a network. According to El-Khatib et al. (2015), a powerful individual in a network might be efficient in reaching others and transferring information, which leads to an improved position for bargaining and negotiation. Two common measures of centrality are constructed in this paper: degree and eigenvector. Degree centrality measures how many nodes an individual is directly connected to. The more direct connections an individual has, the higher his/her degree centrality is. Eigenvector centrality measures how important an individual is within a network. An individual gets a higher eigenvector centrality measure if he/she has more connections with high degree centrality measures.

We identify the CEO for the IPO firm in the IPO year through the BoardEx database.[7] If a firm has two or more co-CEOs in the IPO year, we pick the CEO with the highest centrality measure because we believe that the CEO with the highest centrality measure should have more influence. To make our centrality measures comparable across the years, we construct percentile values for both degree centrality and eigenvector centrality by year, and the value ranges from 0, the lowest centrality, to 99, the highest centrality. The percentile value reflects the ranking position of an individual in the entire network that we use, not just the ranking within the sample CEOs. This transformation enables rank-order comparison of centrality values across different years, even as the annual networks monotonously increase in size. In addition, the percentile transformation allows easier discussion of centrality-related results, especially because the eigenvector centrality values lack clear economic interpretation. In all tables and regression models described below, CEO centrality is utilized in terms of percentages. However, significances of CEO centrality coefficients are similar if we use raw centrality scores instead. We use the centrality measures of the CEOs in the year prior to the firm's IPO year to eliminate the timing concerns about the centrality measures and IPO. In the regression analysis, we use natural logarithm of percentile ranking as the centrality measure because there should be a diminishing marginal effect on the increases in percentile ranking. For example, a CEO increasing her centrality ranking from 50th percentile to 60th percentile should have a greater impact on the firm than another CEO who increases her centrality ranking from 80th percentile to 90th percentile.

Table 1 summarizes the personal characteristics of CEOs in our sample. The mean age of CEOs in our sample is 52, and they have been on the board for an average of 3 years. Average (median) number of CEO

[7] We also use BoardEx to obtain CEO characteristics including their employment history, age, tenure in position, and tenure in company.

connections in our sample is 174 (69). The CEOs have a mean (median) degree centrality percentile of 64 (67) and a mean eigenvector centrality percentile of 65 (67), suggesting that CEOs of IPO firms are better connected compared to "typical" board members of executives of firms around the world.[8]

Table 1 - Summary Statistics of Sample CEOs

This table presents the summary statistics of individual characteristics of the CEOs in sample firms. Mean, median, minimum, maximum and standard deviation are calculated for each individual characteristics variable. Age is the CEO's age in the firm IPO year. Years to retirement is the years to CEO's expected retirement, which is equal to 65. Years in role is the years that the CEO has held the current position. Years on board is the years that the CEO has been on the board. Years in company is the years that the CEO has been working at the current company. Degree centrality is the number of links a CEO has in the year prior to IPO. Degree centrality percentile is the percentile ranking of the CEO in terms of the degree centrality across all individuals in the BoardEx database in the year prior to IPO. Eigenvector centrality percentile is the percentile ranking of the CEO in terms of the eigenvector centrality across all individuals in the BoardEx database in the year prior to the IPO.

Variables	**Mean**	**Median**	**P10**	**P90**	**Standard Deviation**
Age	51.50	51.00	42.00	62.00	7.98
Years in Role	2.21	0.70	0.00	6.50	3.63
Years on Board	2.95	0.80	0.00	7.90	4.75
Years in Company	3.51	0.80	0.00	9.30	5.44
Degree Centrality Score	173.57	68.50	15.00	464.00	249.46
Degree Centrality Percentile	63.62	67.00	27.00	93.00	24.72
Eigenvector Centrality Percentile	64.67	67.00	35.00	92.00	22.06

In addition to CEO centrality percentiles, we introduce another centrality measure: *inefficient networking*. It is assessed based on the relation between CEO's eigenvector centrality percentile and degree centrality percentile. Since eigenvector centrality measures the importance of the connections whereas degree centrality only measures the number of connection, CEOs with efficient networking should rank higher in terms of eigenvector centrality than in degree centrality. We compute the difference between CEOs eigenvector centrality percentile and degree centrality percentile, and create the inefficient network dummy, which takes 1 if the difference is below 33rd percentile within the sample CEOs (that is, the inefficiently networked executives rank high in terms of numbers of total links, but relatively low in terms

[8] On the other hand, there is still a considerable centrality dispersion in our sample. It contains CEOs with degree or eigenvector centralities from the 1st percentile (that is, the second lowest) to the 99th percentile (that is, the highest). The total numbers of CEO (degree) connections range from 1 to 1,815.

of relevance of their connections).

2.2 IPO and firm financial data

We collect data on IPOs from 2001 to 2013 utilizing Thomson Financial's SDC new issues database. We only include IPOs domiciled in U.S. and exclude all close-end funds and unit offerings. The IPOs are excluded if company financial data of is not available in CRSP. We then manually match the IPO firms in SDC database with BoardEx database, and keep those observations that are available in both databases. We further require CEO information to be available on BoardEx in the IPO year. Ultimately, our sample contains 906 IPO firm (and, correspondingly, 906 CEOs). We obtain IPO proceeds, number of shares offered to number of shares outstanding, price revision, underwriter compensation (measured by gross spread), selling concession, whether an IPO is venture backed, Nasdaq return two weeks prior to IPO, and whether the IPO is listed on NYSE from SDC database. We obtain underwriter ranking and firm age data from Jay Ritter's website. We discover whether CEO has bilateral connections with the underwriter prior to the IPO using BoardEx database. Table 2 Panel A shows the distribution of sample IPOs by year. The numbers of our IPOs gradually increase until the time of 2008-2009 financial crisis. Following the substantial drop in IPO filings due to the financial crisis, the annual numbers of sample observations continue to increase until the last sample year, 2013.

We obtain firm financial data from CRSP database. Additionally, we obtain insider trading data and the data for computing CEO overconfidence from Thomson Reuters database. Firm financial data are based on the fiscal year-end prior to the IPO year. Table 2 (Panel B) reports the summary statistics of the sample firm's financial variables and IPO variables.

Table 2 Distribution of Sample IPOs by Year and Summary Statistics of Sample CEOs

Panel A presents the sample distribution of the 906 IPO firms in our sample by IPO year. The number of observations, the percentage of the observations and the accumulative percentage of the observations are calculated by year. Panel B presents summary statistics of a sample of 906 IPO firms from 2001 to 2013. The mean, median, 10th percentile, 90th percentile, standard deviation and number of observations are calculated for each financial variable. Total assets is the total assets of the IPO firm at the end of the fiscal year before IPO. Total revenue is the total revenue of the IPO firm at the end of the fiscal year before IPO. Net income is the net income of the IPO firm at the end of the fiscal year prior to IPO. ROA is the return on assets the fiscal year prior to IPO. Debt ratio is the total debt to total assets at the end of the fiscal year prior to IPO. IPO proceed is the amount the company raise in the IPO. First-day return is the percentage change of the closing price on the IPO day from the offer price. Positive price revision is a dummy variable that takes 1 if the offer price is greater than the middle filing price. Positive insider wealth gain is a dummy variable that takes 1 if insider gain is greater than IPO dilution effect and 0 otherwise.

Panel A

Year	N	Percent	Cum.
2001	18	1.99	1.99
2002	16	1.77	3.75
2003	38	4.19	7.95
2004	121	13.36	21.30
2005	89	9.82	31.13
2006	123	13.58	44.70
2007	103	11.37	56.07
2008	12	1.32	57.40
2009	22	2.43	59.82
2010	74	8.17	67.99
2011	67	7.40	75.39
2012	82	9.05	84.44
2013	141	15.56	100.00
Total	**906**	**100**	

Panel B

Variables	Unit	Mean	Median	p10	p90	Standard Deviation
Total Assets	$ million	1886.60	144.76	21.22	2388.38	12307.00
Total Revenue	$ million	901.82	94.96	1.89	1502.10	5376.69
Net Income	$ million	255.98	0.45	-34.70	54.46	5088.56
ROA		-26.66%	0.19%	-74.24%	15.73%	124.42%
Debt Ratio (Debt/Total Assets)		0.32	0.18	0.00	0.73	0.52
IPO Proceed ($ million)	$ million	310.70	121.90	42.00	529.70	1184.39
First-day return	percentage	13.62%	8.16%	-4.21%	39.06%	21.85%
Positive Price Revision		0.61	1	0	1	0.49
Positive Insider Wealth Gain		0.62	1	0	1	0.48

We measure IPO performance in three ways: first-day return, price revision, and insider wealth gain. The first-day return (that is, IPO underpricing) is measured as the percentage gain at the close price on the first trading day of the IPO as comparing with the offer price. Price revision is measured as the difference between the offer price and the middle filing price for the IPO. Insider wealth gain captures whether the insiders are better-off from the IPO by comparing the appreciation of their holding shares during the IPO and value loss from the selling of their holdings during the IPO. Table 2 (Panel B) shows that the mean (median) IPO underpricing is 13.62% (8.16%). The sample proportions of IPO firms experiencing positive price revision (positive insider wealth gain) are 61% and 62%, respectively.Before performing comprehensive multi-variate analysis of CEO network centrality on IPO performance, we present a univariate analysis of first-day returns. We divide the sample into terciles based on CEO's centrality percentile rankings: top 33% (highest sample centrality percentiles), middle 33%, and bottom 33% (lowest sample centrality percentiles); and compare the initial return between the three subsamples. The results are presented in Table 3. Average first-day IPO return for the most connected CEOs based on degree (eigenvector) centrality is 17.34% (17.33%), which is statistically significantly higher than the average first-day return for the subsample of IPOs with the least connected CEOs, 11.06% (11.88%). Similarly, median first-day IPO returns for the sample of most connected CEOs based on degree (eigenvector) centrality, 10.00% (10.76%) are again significantly higher than the medians for the low centrality CEOs, 6.84% (6.75%). These findings suggest that IPOs managed by well-connected CEOs may be risky and/or highly demanded by investors. Next section will thus provide a more comprehensive multivariate analysis of the effects of CEO centrality on IPO outcomes.

Table 3 Statistics of First-day return by Subsamples

This table presents the mean, median, minimum and maximum of first-day return for the full sample and 3 subsamples split by three different centrality measures of the CEOs. Degree centrality (percentile) is the percentile ranking of the CEO by degree centrality score across all individuals in BoardEx database. Eigenvector centrality (percentile) is the percentile ranking of the CEO by eigenvector centrality score across all individuals in BoardEx database. *** and ** denote the statistical significance of the difference in mean and median between top 33% and bottom 33% of the firms by centrality measures of their CEOs at 1% and 5% levels, respectively.

	Mean	Median	N
	Full Sample		
	13.62%	8.16%	903
	Subsamples by Degree Centrality (Percentile)		
Bottom 33%	11.06%	6.84%	306
Middle 33%	12.51%	6.58%	297
Top 33%	17.34%	10.00%	300
Top - Bottom	6.28%***	3.16**	
	Subsamples by Eigenvector Centrality (Percentile)		
Bottom 33%	11.88%	6.75%	304
Middle 33%	11.67%	6.88%	299
Top 33%	17.33%	10.76%	300
Top - Bottom	5.45%***	4.01%***	

3. CEO Network Centrality and IPO Performance

3.1 Initial IPO Return

One of the most important measures of IPO performance is the return of the stock on the first day of public trading. IPO is risky because of information asymmetries. We expect CEO centrality to be associated with initial IPO returns for several reasons. First, CEOs with high centrality may use their position in the network to efficiently gather and transfer private information so that it creates value for the company in the IPO process. Second, network effect incentivizes CEOs to care more about their reputations. According to Fogel et al. (2015), the existence of network makes it easier for others in the network to penalize the CEO who conducts harmful behaviors to their firms and investors. Many scholars find that this phenomenon is more profound for individuals standing at "the center of the stage" like CEO (see Boot et al. 1993; Burt, 2005; Brass and Labianca, 2006). Moreover, Graham et al. (2005) find that the first career concern for executives is to maintain their reputations. Ultimately, both of the above reasons – easier access to and transfer of private information, as well as reputational effects – suggest that firms run by well-connected CEOs are associated with lower information asymmetry, and lower risk for the investors. Consequently, IPOs run by high centrality CEOs may be associated with low initial return on the first trading day, because underwriter may upward revise the subscription price in conjunction with high demand on the firm's stocks, and IPO investors may not require high underpricing to compensate them for the risk of investment.

On the other hand, CEO centrality can have information asymmetry- and risk-enhancing impact on the IPO firm. EI-Khatib et al. (2015) show that well-connected CEOs can take advantage of their power on the board to influence the decisions of the board and reap private benefits at the expense of shareholders. El-Khatib et al. (2015) also show that CEOs with high centrality are able to avoid market discipline and monitoring. In addition, Liu (2010) argues that CEOs are more likely to find a new position no matter for what reasons they were laid off. Consequently, high CEO centrality may be associated with a high IPO initial return.[9]

Table 4 reports the OLS regression estimates of IPO first-day return on CEO centrality, controlling for IPO and firm characteristics. The dependent variable is the stock return of the firm on the IPO day measured by percentage change from the offer price to the first closing price. The control variable selection follows Cook et al. (2006). Importantly, since Cooney et al. (2015) find that the bilateral connection between CEO and underwriter affects IPO outcome, both for shareholders of the IPO company (in terms of abnormal returns earned) and the underwriters (in terms of their compensation), we control for past relationships between the IPO firm managers and underwriters in this and all subsequent tables by including a dummy variable tracking the presence of such bilateral connections. Model (1) uses degree centrality as CEO centrality measure, model (2) and (3) use eigenvector centrality as CEO centrality measures, and model (3) also adds the inefficient networking dummy. The results in all models show that CEO centrality – both

[9] In this section, our arguments are based on the prevalent view that (high) initial IPO return is primarily linked to (high) information asymmetry and (high) risk. On the other hand, some researchers (e.g. Krigman et al., 2001) consider high underpricing the consequence of excess demand for shares, possibly due to successful marketing of the IPO by underwriters. We address this potential explanation of underpricing in the next section, and find results largely inconsistent with the excess demand driving underpricing in our sample.

degree and eigenvector – is a positively significant determinant of IPO first-day returns. Firms with more central CEOs have significantly higher IPO first-day returns than firms with less central CEOs. The economic significance of CEO centrality measures is high. We find that all else equal, if CEO degree centrality moves from 10^{th} to 95^{th} percentile ranking within our sample, IPO initial return would increase by 5.18 percentage points. If CEO eigenvector centrality moves from 10^{th} to 90^{th} percentile ranking within our sample, IPO initial return would increase by 9.29 percentage points. These are substantial changes given the median 8.16% first-day return for the firms in our sample. The results in model (3) shows that inefficient networking is positively correlated with high IPO initial returns. The results are supportive to our hypothesis that CEO centrality increases the riskiness of IPO and thus results in a higher IPO initial return. Moreover, the results show that inefficient networking further increases the risk of IPO evidenced by increasing 8.83 percentage points, on average, to the initial return of IPO. In all models, we control the firm size effect, IPO characteristics, firm characteristics and the effect of IPO price revision. CEO centrality measures are still positively significant with all the controls. [10]

The results shown in table 4 suggest high CEO centrality may be associated with riskier IPOs, causing the investors to demand higher compensation for their willingness to invest in the form of higher underpricing. However, it is still possible that high underpricing can be a (positive) consequence of increased demand for shares of IPOs managed by high centrality CEOs. Thus, in the next section, we attempt to disentangle these two effects – high risk vs high demand – by studying the relation between CEO centrality, IPO price revisions, and overall IPO wealth effects generated for firm initial investors.

[10] In unreported analysis, we also regress the underwriter compensation, measured by gross spread and selling concessions, on CEO centrality measures controlling for CEO-underwriter relationships. We find that the CEO centrality measure does not significantly impact underwriter compensation.

Table 4 Regression Estimates of IPO Underpricing and CEO Centrality

This table presents the results of OLS regression estimates of first-day return of IPO firms on centrality measures of CEOs, inefficient networking measure and other control variables. The dependent variable is the stock return of the firm on the IPO day measured by percentage change from the offer price to the first closing price. CEO centrality of the IPO firm is degree percentile in column (1), eigenvector percentile in columns (2) and (3). Inefficient networking is a dummy variable. It takes 1 if the value of a CEO's eigenvector centrality percentile minus degree centrality percentile is ranked in bottom 33% of the sample and 0 otherwise. Firm size is measured by natural logarithm of total revenue in the fiscal year prior to the IPO. Float ratio is number of shares offered to number of shares outstanding after IPO. Ln(IPO Proceeds) is the natural logarithms of IPO proceeds of the IPO firm. Underwriter ranking is a dummy variable that takes 1 if the underwriter of the IPO has reputation rank being 8 or higher ranked by Loughran and Ritter (2004) and the data is obtained from Jay Ritter's website: http://bear.warrington.ufl.edu/ritter/ipodata.htm. NYSE is a dummy variable that takes 1 if the IPO is listed on NYSE. Venture backed IPO is a dummy variable that takes 1 if the IPO is venture backed and 0 otherwise. Nasdaq return 2 weeks prior to IPO is the NASDAQ return over the 2 weeks prior to the IPO. Firm age is the years from the firm's founding date, which is obtained from http://bear.warrington.ufl.edu/ritter/FoundingDates.htm, and IPO filing date, which is obtained from SDC. CEO connected with banker is a dummy that takes 1 if CEO has connection with board of the underwriter. Price revision is the change from middle filling price to the offer price. Price revision residual is the residual from the price revision regression. All independent variables and control variables are lagged by one year. All models include year effects. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
Dep. Variable = IPO first-day return	Degree	Eigenvector	Inefficient Networking
Degree	0.0236**		
	(0.0117)		
Eigenvector		0.0423**	0.0576**
		(0.0174)	(0.0224)
Inefficient networking			0.0883**
			(0.0382)
Firm Size	-0.00668	-0.00635	-0.00707
	(0.00747)	(0.00740)	(0.00759)
Float ratio	-127,883***	-129,829***	-130,904***
	(32,540)	(32,708)	(32,913)
Ln(IPO proceeds)	-0.141***	-0.143***	-0.156***
	(0.0522)	(0.0532)	(0.0577)
Underwriter ranking	0.0207	0.0208	0.0208
	(0.0194)	(0.0196)	(0.0196)
NYSE	0.0525**	0.0513**	0.0593**
	(0.0256)	(0.0254)	(0.0277)
Ventured backed IPO	-0.110	-0.114	-0.127*
	(0.0698)	(0.0715)	(0.0759)

Table 4 Regression Estimates of IPO Underpricing and CEO Centrality (Cont.)

	(1)	(2)	(3)
Dep. Variable = IPO first-day return	Degree	Eigenvector	Inefficient Networking
Nasdaq return 2 weeks prior to IPO	-0.00264	-0.00251	-0.00305
	(0.00339)	(0.00335)	(0.00353)
Firm age	0.000836*	0.000839*	0.000832*
	(0.000503)	(0.000504)	(0.000496)
CEO connected with banker	0.0159	0.0149	0.00904
	(0.0374)	(0.0372)	(0.0372)
Price revision	4.258***	4.246***	4.468***
	(1.309)	(1.308)	(1.385)
Price revision residual	-3.664***	-3.651***	-3.877***
	(1.310)	(1.309)	(1.386)
Constant	0.873***	0.808***	0.777***
	(0.294)	(0.267)	(0.252)
Year effects	Y	Y	Y
Observations	890	889	889
R-squared	0.274	0.274	0.274

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.2 Positive price revision

In this section, we investigate the relationship between CEO centrality and positive price revisions of the subscription price from the initial filing price initiated by the underwriters. A positive price revision benefits not only the IPO firm by raising more capital but also increases the wealth of pre-IPO shareholders (Cooney et al., 2015). If CEO centrality has a positive impact on the firm and thus leads to a greater demand for IPO shares, we expect to see a greater likelihood of positive price revisions in firms ran by CEOs with high centrality.

Table 5 shows the Probit regression estimation of the likelihood of a positive price revision on CEO centrality controlling for firm size effects, IPO characteristics, and firm characteristics. The dependent variable is a dummy variable that takes 1 if the IPO has a positive price revision from midpoint of a filing price range and 0 otherwise. Model (1) uses CEO degree centrality, and models (2) and (3) utilize CEO eigenvector centrality. We include other control variables that are important in predicting price revision according to Cook et al. (2006), and also control for the existence of bilateral connections between the IPO firm and the underwriter (Cooney et al. 2015). Our results show that high CEO centrality is associated with *lower* likelihood of positive IPO price revisions (degree centrality insignificantly, but eigenvector centrality significantly at 5% level). This result is economically significant. All else equal, an IPO firm with a within-sample 90th percentile centrality ranked CEO is 15.3% less likely to receive an upward price revision than an IPO firm with a within-sample 10th percentile centrality ranked CEO (a rather substantial increase given the 61% sample unconditional frequency of positive price adjustments).

Table 5 Regression Estimates of IPO Positive Price Revision and CEO Centrality

This table presents the probit regression estimates of positive price revision of IPO firms on centrality measures of CEOs, and other control variables. The dependent variable is a dummy variable that takes 1 if there is a positive price revision from middle filling price to offer price and 0 otherwise. CEO centrality of the IPO firm is degree percentile in column (1), and eigenvector percentile in columns (2) and (3). Inefficient networking is a dummy variable. It takes 1 if the value of a CEO's eigenvector centrality percentile minus degree centrality percentile is ranked in bottom 33% of the sample and 0 otherwise. Firm size is measured by natural logarithm of total revenue in the fiscal year prior to the IPO. Ln(IPO Proceeds) is the natural logarithms of IPO proceeds of the IPO firm. NYSE is a dummy variable that takes 1 if the IPO is listed on NYSE. Venture backed IPO is a dummy variable that takes 1 if the IPO is venture backed and 0 otherwise. Nasdaq return 2 weeks prior to IPO is the NASDAQ return over the 2 weeks prior to the IPO. Firm age is the years from the firm's founding date, which is obtained from http://bear.warrington.ufl.edu/ritter/FoundingDates.htm, and IPO filing date, which is obtained from SDC. CEO connected with banker is a dummy that takes 1 if CEO has connection with board of the underwriter. All independent variables and control variables are lagged by one year. All models include year effects. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Variable = Prob(positive offer price revision)	(1) Degree	(2) Eigenvector	(3) Inefficient Networking
Degree	-0.0790		
	(0.0875)		
Eigenvector		-0.193**	-0.215**
		(0.0943)	(0.0975)
Inefficient networking			-0.147
			(0.0944)
Firm Size	0.00336	0.00310	0.00257
	(0.0304)	(0.0305)	(0.0304)
Ln(IPO proceeds)	0.426***	0.434***	0.441***
	(0.0652)	(0.0661)	(0.0665)
NYSE	-0.232**	-0.228**	-0.238**
	(0.114)	(0.115)	(0.114)
Ventured backed IPO	0.321***	0.341***	0.345***
	(0.105)	(0.105)	(0.105)
Nasdaq return 2 weeks prior to IPO	0.0217	0.0212	0.0214
	(0.0144)	(0.0144)	(0.0144)
Firm age	-0.00261	-0.00259	-0.00242
	(0.00201)	(0.00200)	(0.00201)
CEO connected with banker	0.0164	0.0365	0.0483
	(0.194)	(0.193)	(0.194)
Constant	-1.613***	-1.193**	-1.060*
	(0.532)	(0.541)	(0.557)

Table 5 Regression Estimates of IPO Positive Price Revision and CEO Centrality (Cont.)

Year effects	Y	Y	Y
Observations	906	905	905

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results do not support the hypothesis that high CEO centrality has a risk-reducing impact on the IPO firm. Rather, firms with high centrality CEO are perceived as riskier and thus its IPO need to be underpriced more to compensate the risk that investors are bearing. Therefore, the underwriter is thus less likely to revise the subscription price upward.

3.3 Insider wealth gain

According to Loughran and Ritter (2002), Bradley and Jordan (2002) and Cooney et al. (2015), initial return and price revision do not show a comprehensive picture of IPO performance. Pre-IPO shareholders' main goal is to obtain wealth gain through the IPO. Hence, a successful IPO should gain wealth for the insiders. We examine whether high centrality CEO is associated with positive wealth gain for the pre-IPO shareholders. If CEO's high centrality has a positive effect on IPO firm, it should be associated with higher likelihood of pre-IPO shareholder gaining wealth and vice versa. Pre-IPO shareholders' wealth increases when IPO firm has a positive price revision from initial filling price and positive return on the first day of trading for the shares that they retain from pre-IPO to post-IPO. Pre-IPO shareholders lose wealth when they sell the shares at the offer price and the price per share increases thereafter, which cause them "leave the money on the table". We compute pre-IPO shareholders' wealth gain from retained shares net of wealth loss from sold shares in IPO. That is, the wealth gain is defined as:

$$\textit{Wealth effect} = (1^{st}\textit{ day closing price} - \textit{midpoint of filling price range}) \times \textit{shares retained} - (1^{st}\textit{ day closing price} - \textit{offer price}) \times \textit{shares sold}$$

We investigate if high centrality CEO is associated with high likelihood of positive wealth gain by pre-IPO shareholders. (Cooney et al. (2015) perform a similar analysis in their investigation of bilateral links between IPO firms and underwriters.)

Table 6 shows the results of probit regression of probability of positive wealth gain by pre-IPO shareholders on CEO centrality, IPO characteristics, firm characteristics and connection between CEO and underwriter's board members. Model (1) uses degree centrality as CEO centrality measure, model (2) and (3) use eigenvector centrality as CEO centrality measures, and model (3) adds inefficient networking dummy. The selection of control variables follows Cook et al. (2006). The results show CEO centrality is negatively associated with the likelihood of positive wealth gain by the pre-IPO shareholders (degree centrality not significantly, but eigenvector centrality significantly at 5% level). This suggests that high CEO centrality does not benefit pre-IPO shareholders during the IPO process, and is consistent with our findings in previous tables showing that IPO firms managed by well-connected CEOs have greater IPO underpricing and lower likelihood of positive subscription price revisions. Model (3) further indicates that inefficient networking also significantly reduces the likelihood of positive wealth gain by the pre-IPO shareholders.

Our findings are economically significant. All else equal, a firm with a CEO at the 90th percentile centrality ranking in our sample would have 18.0 percentage points less likely to have a positive wealth gain by pre-IPO shareholders than a firm with a CEO at the 10th percentile centrality ranking (a substantial change given the unconditional sample frequency of IPOs with a positive wealth effect is equal to 62.4%).

Overall, our findings in Tables 3-6 provide evidence on significant links between CEO centrality and firm's IPO performance. High centrality CEOs are associated with high IPO underpricing for the firm. The high underpricing of those IPOs does not indicate the success of the IPO marketing. Instead, it reflects the higher risk the market perceives, implying a larger discount in the offer price. The higher risk of IPOs managed by high centrality CEOs is further evidenced by a lower likelihood of positive IPO price revisions and lower likelihood of pre-IPO shareholders' wealth gains. Additionally, we find evidence that high underpricing, low likelihood of positive price revisions, and lower likelihood of pre-IPO shareholders' wealth gains are all further exacerbated if CEOs are inefficiently networked – that is, if they have many connections with little overall importance for the network.

Table 6 Regression Estimates of Positive Insider Wealth Effects and CEO Centrality

This table presents the probit regression estimates of insider wealth gain of IPO firms on centrality measures of CEOs, efficient networking measures of CEOs and other control variables. The dependent variable is a dummy that takes 1 if there is an insider wealth gain and 0 otherwise. Follow Cook et al. (2006), we define insider wealth gain as the wealth effects of IPO minus dilution effects of IPO. CEO centrality of the IPO firm is degree percentile in column (1), eigenvector percentile in columns (2) and (3). Inefficient networking is a dummy variable. It takes 1 if the value of a CEO's eigenvector centrality percentile minus degree centrality percentile is ranked in bottom 33% of the sample and 0 otherwise. Firm size is measured by natural logarithm of total revenue in the fiscal year prior to the IPO. Float ratio is number of shares offered to number of shares outstanding after IPO. Ln(IPO Proceeds) is the natural logarithms of IPO proceeds of the IPO firm. CEO connected with banker is a dummy that takes 1 if CEO has connection with board of the underwriter. Firm age is the years from the firm's founding date, which is obtained from http://bear.warrington.ufl.edu/ritter/FoundingDates.htm, and IPO filing date, which is obtained from SDC. Residual of initial return is the residual from the initial return regression. All independent variables and control variables are lagged by one year. All models include year effects. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
Dep. Variable = Prob(positive insider wealth gain)	Degree	Eigenvector	Inefficient Networking
Degree (Percentile)	-0.0494		
	(0.0898)		
Eigenvector		-0.216**	-0.246***
		(0.0891)	(0.0912)
Inefficient networking			-0.175*
			(0.0996)
Firm Size	0.0315	0.0280	0.0258
	(0.0293)	(0.0295)	(0.0294)
Float ratio	-1.066e+06***	-1.161e+06***	-1.186e+06***
	(262,866)	(261,927)	(265,390)
Ln(IPO proceeds)	0.380***	0.395***	0.402***
	(0.0620)	(0.0633)	(0.0635)
CEO connected with banker	0.0459	0.0813	0.0986
	(0.205)	(0.205)	(0.206)
Firm age	-0.00622***	-0.00616***	-0.00605***
	(0.00212)	(0.00212)	(0.00213)
Residual of initial return	3.106***	3.123***	3.144***
	(0.323)	(0.324)	(0.326)
Constant	-0.866	-0.206	-0.0309
	(0.562)	(0.553)	(0.568)
Year effects	Y	Y	Y
Observations	890	889	889

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.4 Post-IPO CEO Turnover

The managerial labor market offers a mechanism that disciplines the senior managers in order to work in the interest of the shareholders. Well-governed firms optimally fire managers associated with poor firm performance (e.g. Jenter and Kanaan, 2015). However, if well-connected CEOs are able to utilize their influence and power to gain more secure entrenchment, then managerial labor market fails its important governance role, and the IPOs lead by such CEOs may be perceived inherently more risky, which may indeed lead to higher underpricing and lower likelihood of positive price adjustments, as well as positive wealth effects described in Tables 4-6.

Following Jenter and Kanaan (2015) and El-Khatib et al. (2015), we use Cox Hazard model to test how post-IPO stock performance (measured by the one-year abnormal stock return after the IPO) impact the odds of the CEO leaving the firm after the IPO. We obtain CEO turnover data by examining their employment history in the BoardEx database. Of the final sample of 597 CEOs based on data availability, 198 were replaced during the first three years post-IPO.[11] We utilize the following specification of Cox Hazard model:

$$
\begin{aligned}
&(\text{CEO Turnover} = 1|X_i) \\
&\qquad = \alpha + \beta_1 Abnormal\ return + \beta_2 Centrality \\
&\qquad + \beta_3 Abnormal\ return \times High\ centrality \\
&\qquad + \beta_4 Abnormal\ return \times (1 - High\ centrality) + \beta_5 Age + \beta_6 F_i \\
&\qquad + \beta_7 Crisis\ year\ dummy + \varepsilon_i
\end{aligned}
$$

where the dependent variable is the hazard rate of CEO turnover in the sample period. The one-year abnormal return is the stock return of the IPO firm from the first closing day to the 12th month after the IPO month in excess of a value-weighted market portfolio return. High centrality is a dummy variable that takes 1 if the CEO's centrality measure falls in the top 33% of the sample and 0 otherwise. CEO age is the age

[11] Due to a relatively small IPO sample size, we retain all CEO replacements, not just "disciplinary", defined by Parrino (1997) to be replacement that are not due to CEO retirement or reassignment within a company (e.g. CEO move to the Chairman of Board). However, our results are qualitatively similar, albeit less significant, if utilize just disciplinary turnovers in our analysis.

of CEO at the time of IPO. Firm size is the total revenue of the IPO company in the fiscal year prior to the IPO. Tobin's q is calculated as the sum of the market value of equity (price per share at the end of the fiscal year of IPO multiply by the number of shares outstanding), total liability, and the liquidating value of preferred stock, all divided by the book value of the total assets. F_i is a vector of firm specific financial characteristics. Industry fixed effect is a series of dummy variables indicating the industry of the IPO firm. Crisis year dummy takes value 1 if the firm's IPO is in year 2008 or 2009 and 0 otherwise.

The results are presented in Table 7. Consistent with previous literature (e.g. Jenter and Kanaan, 2015), Model 1 shows that the likelihood of CEO turnover is negatively correlated with post-IPO performance, suggesting that CEOs with poorer firm long-term performance are more likely to be replaced. However, Models 2 and 3 suggest that only low centrality CEOs tend to be replaced in case of poor stock returns, as evidenced by significantly negative coefficients for Abnormal Return*[1- High Centrality dummy]. The coefficient measuring the turnover-performance sensitivity for the subsample of high centrality CEOs (measured by Abnormal Return*[High Centrality dummy] coefficient) is insignificant. Models 2 and 3 further show that centrality per se is an insignificant determinant of CEO turnover. Ultimately, our findings suggest that well-connected CEOs are able to utilize their influence and power to solidify their entrenchment in the post-IPO firm. [12]

3.5 CEO Centrality and Insider Trading

Finance literature documents that sales of firm's shares initiated by company's insiders are associated with a negative signal about the future firm value (Seyhun 1992; Clarke et al. 2001). We test if CEOs with high centrality are more likely to take advantage of insider information and execute sales that are followed by low abnormal stock returns. If so, investing in firms run by CEOs with high centrality should be perceived as risky, and the company such CEOs lead should have high underpricing, low probability of positive price revision and low probability of wealth gain to the existing shareholders during the IPO.

[12] In unreported analysis, we get similar results if we replace post-IPO abnormal stock returns with post-IPO accounting returns as the measure to determine performance-turnover sensitivity.

Table 7 Cox Hazard Regression Estimates of CEO Turnover

This table presents the estimation results of the Cox Hazard regression model to predict the CEO turnover after an IPO between 2001 and 2014. The dependent variable is the hazard rate of CEO turnover in the sample period. The CEO turnover is measured in the 3 years post-IPO. The 1-year abnormal return is the stock return of the IPO firm from the first closing day to the 12^{th} month after the IPO month in excess of a value-weighted market portfolio return, respectively. High centrality is a dummy variable that takes 1 if the CEO's centrality measure falls in the top 33% of the sample and 0 otherwise. CEO age is the age of CEO at the time of IPO. Firm size is the total revenue of the IPO company in the fiscal year prior to the IPO. Tobin'q is calculated as the sum of the market value of equity (price per share at the end of the fiscal year of IPO multiply by the number of shares outstanding), total liability, and the liquidating value of preferred stock, all divided by the book value of the total assets. Industry fixed effect is a series of dummy variables indicating the industry of the IPO firm. Crisis year effect takes value 1 if the firm's IPO is in year 2008 or 2009 and 0 otherwise. Robust standard errors are included in the parentheses. ***, **, and * denote statistical significance from zero at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
Dep.variable = Prob(CEO turnover)		Eigenvector	Degree
1-year Abnormal Return	-6.668***		
	(1.824)		
Degree			0.199
			(0.153)
Eigenvector		-0.0431	
		(0.160)	
1-year Abnormal Return * (1 - High Centrality)		-6.933***	-7.659***
		(2.079)	(2.193)
1-year Abnormal Return * High Centrality		-5.560	-4.848
		(3.667)	(3.387)
CEO Age	0.00465	0.00443	0.00482
	(0.00872)	(0.00876)	(0.00885)
Firm Size	-0.000138*	-0.000137*	-0.000151*
	(7.92e-05)	(7.89e-05)	(8.15e-05)
Tobin's Q	-0.00284	-0.00368	-0.00395
	(0.0354)	(0.0353)	(0.0358)
Industry Fixed Effect	Yes	Yes	Yes
Crisis Year Effect	Yes	Yes	Yes
Observations	597	596	597

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We analyze the stock performance following the sales executed by the CEOs in our sample within 1 year after the IPO. We use three- and two-month abnormal return to measure the stock performance. In

Table 8, we find that CEOs with high centrality are associated with lower three-month and two-month abnormal returns following a sale. The results hold after controlling for the size effect of the firm and the IPO, as well as the industry fixed effect using 4-digit SIC code of the company. Therefore, our findings provide supporting evidence as for why firms led by CEOs with high centrality are perceived as riskier.

Table 8 Post-Insider Sale Performance and CEO Centrality

This table presents the OLS regression estimates of post-insider sale abnormal returns on the centrality measures, size of firm and IPO, and industry effect dummies as control variables. The dependent variable for columns (1) and (3) is three-month abnormal return of the security following an insider sale. The dependent variable for columns (2) and (4) is two-month abnormal return of the security following an insider sale. Firm size is measured by natural logarithm of total revenue in the fiscal year prior to the IPO. Ln(IPO Proceeds) is the natural logarithms of IPO proceeds of the IPO firm. Industry fixed effect is a series of dummy variables indicating the industry of the IPO firm using 4-digit SIC code. Robust standard errors are included in the parentheses. ***, **, and * denote statistical significance from zero at the 1%, 5% and 10% levels, respectively.

	(1) Three-month Abnormal Return	(2) Two-month Abnormal Return	(3) Three-month Abnormal Return	(4) Two-month Abnormal Return
Degree	-0.0705**	-0.0646***		
	(0.0289)	(0.0223)		
Eigenvector			-0.0594*	-0.0557**
			(0.0351)	(0.0264)
Firm Size	8.14e-05	6.95e-05	7.09e-05	6.03e-05
	(4.96e-05)	(4.22e-05)	(4.97e-05)	(4.31e-05)
Ln(IPO proceeds)	-0.000510	-0.00481	-0.00123	-0.00547
	(0.00606)	(0.00428)	(0.00595)	(0.00421)
Constant	0.201	0.220**	0.161	0.188*
	(0.125)	(0.0918)	(0.146)	(0.105)
Industry Fixed Effects	Y	Y	Y	Y
Observations	1,173	1,173	1,173	1,173
R-squared	0.251	0.222	0.248	0.218

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.6 Endogeneity and Centrality Determinants

3.6.1 Instrumental variable analysis

In our paper, we suggest a causal relation between CEO centrality and IPO outcomes. While it is not likely that the execution of IPO affects CEO centrality directly, we still want to consider the possibility that, for example, greater underpricing benefitting new shareholders may give CEO opportunity to enhance his or her network due to new relationships with these investors. We thus utilize an instrumental variable approach to study the causal relationship between CEO centrality and IPO performance. In the first stage of the analysis, we use two instrumental variables that are directly related to CEO centrality but are unlikely to affect the IPO outcomes to create the instrumented centralities. We use the mean centrality of other CEOs in the same state[13] as the IPO firm, and the IPO firm's corporate social responsibility index[14] (CSR) as the instrumental variables for the CEO centrality. Then, in the second stage, we use the instrumented centrality to regress IPO performance. Table 9 presents the results of the instrumental variable approach analysis. Panel A columns (1) and (2) show the first stage of the analysis. The two instrumental variables are positively significant in predicting CEO centralities. The columns (3) and (4) in Table 9 reports the analysis of IPO underpricing using the instrumented CEO degree and eigenvector centralities, respectively. We show that both instrumented centrality measures are highly significant[15]. The Panels B and C of Table present the regression estimations of the probabilities of positive offer price revision and insider wealth gain, respectively. The instrumented centrality measures in those results are all highly significant with the same sign as in our main analysis reported in Table 5 and 6. Therefore, possible endogeneity thus likely does not create interpretation issues for the results reported in this paper.

[13] We collect the centrality of all the S&P 1500 firms in the same state as the IPO firm in the same year of the IPO, and calculate the mean of the CEOs' centrality.
[14] We follow Lins, Servaes, and Tamayo (2017) to create an index ranges from -5 to 5 to reflect the firm's performance in community, diversity, employee relations, environment, and human rights, and use the median index within the sample period for each firm.
[15] It is not surprising, though, that the coefficients of the instrumented centrality measures are larger than those of the centrality measures because the instrumented centrality measures are the local average of the centrality conditional on the centrality determinants and that the standard error of the coefficient estimation is significantly larger, which is the price to pay for a variable to be considered as endogenous (Wooldridge 2015).

Table 9 Instrumental Variable Approach Analysis of IPO Performance

This table presents the results of the instrumental variable approach analysis of IPO Performance. Panel A columns (1) and (2) presents the regression results of the CEO centrality with instrumental variables. Mean Degree (Eigenvector) Centrality of CEOs in Same State is the average of all CEOs of the S&P 1500 firms in the same state as the IPO firm in the same year. Firm CSR is the median of the company's social responsibility index based on Lins et al. (2017) across all sample period. Columns (3) and (4) presents the results of OLS regression estimates of first-day return of IPO firms on instrumented centrality measures of CEOs and other control variables. Panel B presents the result probit regression estimates of positive price revision of IPO firms on instrumented centrality measures of CEOs, and other control variables. The dependent variable is a dummy variable that takes 1 if there is a positive price revision from middle filling price to offer price and 0 otherwise. Panel C presents the probit regression estimates of insider wealth gain of IPO firms on instrumented centrality measures of CEOs, and other control variables. The dependent variable is a dummy that takes 1 if there is an insider wealth gain and 0 otherwise. All other variables are as previously explained. All models include year effects. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Instrumented Centrality and IPO Underpricing

Dep. Variable = IPO first-day return	(1) Degree Centrality	(2) Eigenvector Centrality	(3) IPO Underpricing	(4) IPO Underpricing
Mean Degree Centrality of CEOs in Same State	0.0193***			
	(0.00531)			
Mean Eigenvector Centrality of CEOs in Same State		0.0155***		
		(0.00508)		
Firm CSR	0.115*	0.141**		
	(0.0601)	(0.0549)		
Instrumented Degree Centrality			1.828**	
			(0.834)	
Instrumented Eigenvector Centrality				1.108**
				(0.551)
Firm Size	0.0233	0.0150	-0.0801**	-0.0352*
	(0.0186)	(0.0114)	(0.0403)	(0.0208)
Float ratio	-358,453**	-289,516	-63,927	-95,378**
	(155,684)	(188,721)	(44,242)	(47,680)
Ln(IPO proceeds)	0.0163	0.0171	-0.181**	-0.118*
	(0.0358)	(0.0263)	(0.0898)	(0.0640)
Underwriter ranking	0.0779	0.129	-0.0287	-0.0307
	(0.0931)	(0.113)	(0.0229)	(0.0227)
NYSE	0.0372	0.0501	0.0242	0.00584
	(0.0474)	(0.0400)	(0.0210)	(0.0182)
Ventured backed IPO	0.144***	0.105**	-0.546*	-0.276
	(0.0544)	(0.0502)	(0.286)	(0.171)
Price revision	-0.285*	-0.277**	4.504**	2.941**
	(0.147)	(0.134)	(1.947)	(1.272)
Firm age	0.000793	0.000397	-0.000476	8.68e-05
	(0.000640)	(0.000590)	(0.000354)	(0.000439)

Table 9 Instrumental Variable Approach Analysis of IPO Performance (Cont.)

Dep. Variable = IPO first-day return	(1) Degree Centrality	(2) Eigenvector Centrality	(3) IPO Underpricing	(4) IPO Underpricing
Price revision residual			-3.780*	-2.239*
			(1.945)	(1.272)
CEO connected with banker			-0.0604	-0.0420
			(0.0442)	(0.0399)
Nasdaq return 2 weeks prior to IPO			-0.00633	-0.00271
			(0.00556)	(0.00419)
Constant	2.535***	2.782***	-5.707**	-3.401*
	(0.417)	(0.402)	(2.635)	(1.753)
Observations	629	629	628	628
Adjusted R-squared	0.076	0.070	0.256	0.251

Panel B: Instrumented Centrality and IPO Positive Price Revision

Dep. Variable = Prob(positive offer price revision)	(1) Degree	(2) Eigenvector
Instrumented Degree Centrality	-3.366***	
	(0.595)	
Instrumented Eigenvector Centrality		-3.699***
		(0.586)
Ln(IPO proceeds)	0.538***	0.574***
	(0.0959)	(0.0981)
Firm Size	0.119***	0.0918**
	(0.0417)	(0.0402)
NYSE	-0.175	-0.126
	(0.147)	(0.148)
Ventured backed IPO	1.053***	1.011***
	(0.176)	(0.164)
Nasdaq return 2 weeks prior to IPO	0.0186	0.0211
	(0.0171)	(0.0171)
Firm age	-0.000975	-0.00229
	(0.00247)	(0.00236)
CEO connected with banker	-0.0499	-0.0160
	(0.239)	(0.232)
Constant	10.57***	11.81***
	(2.365)	(2.319)
Observations	629	629
Pseudo R-squared	0.133	0.140

Panel C: Instrumented Centrality and Insider Wealth Effect

Dep. Variable = Prob(positive insider wealth gain)	(1) Degree	(2) Eigenvector
Instrumented Degree Centrality	-1.868***	
	(0.556)	

Table 9 Instrumental Variable Approach Analysis of IPO Performance (Cont.)

Dep. Variable = Prob(positive insider wealth gain)	(1) Degree	(2) Eigenvector
Instrumented Eigenvector Centrality		-2.839***
		(0.589)
Ln(IPO proceeds)	0.365***	0.415***
	(0.0847)	(0.0864)
Firm Size	0.0347	0.0228
	(0.0375)	(0.0382)
Float ratio	-1.557e+06***	-1.859e+06***
	(431,599)	(418,025)
CEO connected with banker	0.143	0.193
	(0.242)	(0.236)
Firm age	-0.00566**	-0.00618***
	(0.00237)	(0.00231)
Residual of initial return	2.726***	2.863***
	(0.378)	(0.388)
Constant	6.955***	10.81***
	(2.378)	(2.471)
Observations	628	628
Pseudo R-squared	0.129	0.146

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.6.2 Centrality determinants and excess centrality

In this paper, we argue that higher underpricing, lower likelihood of positive price revisions, and lower likelihood of positive wealth effects for the pre-IPO shareholders are all due to CEOs who have superior network positions, and thus are likely to possess greater "social capital." At the same time, CEOs who have superior skills – and thus possess greater "human capital" – may have easier time networking, as many individuals likely enjoy being connected to skilled managers. Simultaneously, more skilled CEOs may have superior entrenchment abilities, greater opportunities to benefit from their insider trades, etc. Consequently, our findings of links between CEO centrality and IPO outcomes may also be due to CEO human capital, and not just CEO network-related social capital. In this section, we address whether the relations attributed to network centrality in our paper may be partially due to omitted variables associated with centrality (both individual characteristics and firm-specific variables) in addition to network effects captured by centrality.

In order to analyze the role of potentially omitted centrality determinants, we employ the "excess centrality" developed by El-Khatib et al. (2015). "Excess centrality" is defined as the residual from regression of centrality (degree or eigenvector) on CEO personal attributes and firm characteristics. A CEO with high "excess centrality" should be again considered influential and powerful, but "excess centrality" is now unrelated to the individual- and firm-related determinants of centrality.

We rerun all of the models presented in Tables 4-6 with centrality variables replaced by "excess centrality". The centrality determinants considered include: (a) number of boards of public and private firms the CEO is a member of, (b) number of sectors the CEO worked in, (c) CEO age, (d) CEO tenure on the company's board, and (e) firm's (sales) size. The results are shown in Table 10 Panels A, B, and C for the estimations of IPO underpricing, probability of positive offer price revision, and probability of insider wealth gain, respectively. Our results have very similar high significances, and identical signs, suggesting that the centrality measures indeed reflect the impact of CEO network (social capital) effects, as opposed to the impact of omitted variables.

Table 10 Analysis of IPO Performance and Excess Centrality

This table presents the results of the analysis of IPO Performance on excess CEO centrality measures. Excess centrality is defined as the residual from regression of centrality (degree or eigenvector) on number of boards of public and private firms the CEO is a member of, number of sectors the CEO worked in, CEO age, CEO tenure on the company's board, and firm's (sales) size. Panel A presents the results of OLS regression estimates of first-day return of IPO firms on excess centrality measures of CEOs and other control variables. Panel B presents the result probit regression estimates of positive price revision of IPO firms on excess centrality measures of CEOs, and other control variables. The dependent variable is a dummy variable that takes 1 if there is a positive price revision from middle filling price to offer price and 0 otherwise. Panel C presents the probit regression estimates of insider wealth gain of IPO firms on excess centrality measures of CEOs, and other control variables. The dependent variable is a dummy that takes 1 if there is an insider wealth gain and 0 otherwise. All other variables are as previously explained. All models include year effects. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Excess Centrality and IPO Underpricing		
	(1)	(2)
Dep. Variable = IPO first-day return	Degree	Eigenvector
Excess Degree Centrality	0.0420**	
	(0.0190)	
Excess Eigenvector Centrality		0.0567**
		(0.0266)
Firm Size	-0.0117	-0.0106
	(0.00985)	(0.00957)
Float ratio	-104,565***	-107,264***
	(31,946)	(32,182)
Ln(IPO proceeds)	-0.0981*	-0.0962*
	(0.0527)	(0.0530)
Underwriter ranking	0.0193	0.0194
	(0.0186)	(0.0188)
NYSE	0.0309	0.0291
	(0.0245)	(0.0242)
Ventured backed IPO	-0.0854	-0.0829
	(0.0721)	(0.0726)
Nasdaq return 2 weeks prior to IPO	0.00101	0.00135
	(0.00263)	(0.00254)
Price revision	3.660***	3.541**
	(1.408)	(1.380)
Firm age	0.000726	0.000710
	(0.000588)	(0.000589)
CEO connected with banker	-0.0176	-0.0159
	(0.0346)	(0.0341)
Price revision residual	-3.096**	-2.977**
	(1.411)	(1.383)
Constant	0.749**	0.734**
	(0.334)	(0.335)
Observations	782	781
Adjusted R-squared	0.243	0.242

Table 10 Analysis of IPO Performance and Excess Centrality (Cont.)

Panel B: Excess Centrality and IPO Positive Price Revision		
	(1)	(2)
Dep. Variable = Prob(positive offer price revision)	Degree	Eigenvector
Excess Degree Centrality	-0.0878	
	(0.0986)	
Excess Eigenvector Centrality		-0.202*
		(0.103)
Ln(IPO proceeds)	0.416***	0.421***
	(0.0713)	(0.0721)
Firm Size	0.00383	0.00430
	(0.0322)	(0.0323)
NYSE	-0.209*	-0.207*
	(0.126)	(0.126)
Ventured backed IPO	0.247**	0.267**
	(0.111)	(0.112)
Nasdaq return 2 weeks prior to IPO	0.0122	0.0113
	(0.0152)	(0.0152)
Firm age	-0.00293	-0.00297
	(0.00209)	(0.00208)
CEO connected with banker	-0.00116	0.00781
	(0.209)	(0.208)
Constant	-1.830***	-1.863***
	(0.440)	(0.443)
Observations	798	797
Pseudo R-squared	0.0698	0.0720

Panel C: Excess Centrality and Insider Wealth Effect		
	(1)	(2)
Dep. Variable = Prob(positive insider wealth gain)	Degree	Eigenvector
Excess Degree Centrality	-0.0730	
	(0.101)	
Excess Eigenvector Centrality		-0.238**
		(0.0960)
Ln(IPO proceeds)	0.414***	0.424***
	(0.0690)	(0.0704)
Firm Size	0.0367	0.0343
	(0.0323)	(0.0325)
Float ratio	-954,628***	-1.038e+06***
	(276,521)	(273,534)
CEO connected with banker	0.0769	0.0975
	(0.221)	(0.220)
Firm age	-0.00666***	-0.00671***
	(0.00222)	(0.00223)
Residual of initial return	3.739***	3.767***
	(0.394)	(0.396)

Table 10 Analysis of IPO Performance and Excess Centrality (Cont.)

Constant	-1.276***	-1.279***
	(0.440)	(0.444)
Observations	782	781
Pseudo R-squared	0.169	0.172

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.7 Robustness Analysis

3.7.1 Firm size effect

High centrality CEOs are more likely to manage larger firms. To control for the possibility that our centrality variables proxy for potentially non-linear size effects, in unreported analysis we utilize three methods used by El-Khatib et al. (2015): (a) we add a "large firm size" dummy, (b) we add a quadratic size variables, and (c) we split our sample into two subsamples based on firm size, Regardless of the method utilized, CEO centrality remains significant determinant of IPO underpricing (Table 4), likelihood of positive price revisions (Table 5), and likelihood of positive insider IPO wealth effects (Table 6). Consequently, it is unlikely that our findings are due to the firm size effect.

3.7.2 The impact of CEO overconfidence

Overconfident people may be more likely to build large personal networks. Consequently, high CEO centrality may be positively related to overconfidence. Finance literature finds that overconfident CEOs tend to make decisions that are not to the best interest of the shareholders. For example, Malmendier and Tate (2008) and Roll (1986) find that CEO overconfidence may cause losses in mergers and acquisition. Malmendier and Tate (2005) find that overconfident CEOs tend to overestimate the return of the investment and overinvest. As our paper suggest that high-centrality CEOs may be associated with risky IPOs less likely to generate benefits for existing shareholders, we need to address the potential positive link between CEO centrality and overconfidence.

In order to separate CEO network effects (proxied by centrality) and overconfidence, in unreported analysis, we include overconfidence measures in all of our models in Tables 4-6. The overconfidence measures are constructed following the models from Otto (2014) and Malmendier and Tate (2008).[16] The inclusion of any of the overconfidence measures does not change the signs and high significance levels of the centrality coefficients. In addition, we uncover that overconfidence and centrality are negatively correlated in our sample. Consequently, our results regarding the role of CEO centrality in the IPO process are unlikely to be due to CEO overconfidence.

3.7.3 The impact of CEO age

It may be possible that our findings regarding CEO centrality may be due to firms trying to hire experienced and "visible" CEO right before the firm's IPO. Thus, in unreported analysis, we include CEO's age and years in position and interact with centrality measures in our models. The original centrality determinants retain the same signs and very similar significances as those reported in Tables 4-6, while the interactive coefficients are mostly insignificant. Moreover, we find that the coefficient for the years in position is not statistically significant. Hence, we find evidence that our results are neither determined by CEO tenure, nor driven by firms seeking high centrality CEOs right before IPO.

4. Conclusion

We show that CEO network centrality is statistically and economically meaningful determinant of IPO outcomes. IPOs of firms with high centrality CEOs are associated with significantly greater underpricing returns. These IPOs also have a lower likelihood of positive offer price adjustments from their initial filing range, as well as a lower likelihood of generating positive net IPO wealth effects for the pre-IPO shareholders. Our results suggest that new investors may perceive IPOs with well-connected CEOs as riskier. In addition, we find that well-connected CEOs are less likely to be replaced in case of poor post-IPO performance, consistent with higher entrenchment of high centrality CEOs in post IPO firms. Also, we show that high centrality CEOs are more likely to sell company's stock for personal benefit at the cost of the shareholders, indicated by a lower abnormal return following their personal sales of the securities. These

[16] Malmendier and Tate (2008) identify overconfident executives based on their decision to hold (rather than optimally exercise) their in-the-money options. Otto (2014) utilizes firm's voluntary earnings forecasts to classify overconfident managers.

findings are consistent with high centrality CEOs being able to utilize their influence and power derived from higher positions within the social network hierarchy to entrench themselves and to thwart optimal corporate governance. Last, we document additional risks associated with CEOs who network "inefficiently" (that is, whose networks have many links, but lack influential connections). Namely, underpricing is higher, and the chance of positive net wealth effects lower for IPOs with low eigenvector centrality CEOs, if they also have high degree centralities.

We contribute to the growing literature on social networks in finance. Our paper is the first to show that individual position within social network hierarchy – which leads to higher influence and power, and can be proxied by social network centrality – affects IPO outcomes. We provide an extension of previous research chiefly based on bilateral connections (e.g. Engelberg et al. 2012; Ishii and Xuan, 2014; Cai and Sevilir, 2012; Cohen et al., 2010). In addition, our results are consistent with *detrimental* impact of CEO centrality on wealth of pre-IPO shareholders, and thus they provide an important contrast to existing research on social networks in the context of IPO, which has so far mainly documented benefits of networks due to bilateral connections between IPO managers and underwriters (Cooney et al., 2015), or due to high firm-specific centrality of underwriters (Chuluun, 2015).

Chapter 2

Personal Connections, Financial Advisors, and M&A Outcomes

1. Introduction

Merge and Acquisitions (M&A) are some of the most important decisions a firm's leadership could make, and they do not usually make the decisions on their own, but rather consult an outside advisor (Bao & Edmans 2011). Given the substantial value implication that an M&A deal could have on the shareholder, it is crucial that the financial advisor hired in the process could have effective functions in assessing, negotiating, and executing or halt the deal. The firm's leadership and the board should also have a strong responsibility on the due diligence. Most importantly, such efforts from the financial advisor and the firm should not be diminished by the potential conflict of interest or collusion as a result of the social ties between the bidder firm's leadership and that of the financial advisor. In this paper, we examine how the personal social ties between a firm's top leadership, which are CEO, CFO, COO, the President, and the Chair of the Board, and those of the financial advisor affects the M&A performance of the bidder firm.

Whether and how do financial advisors matter in a merge and acquisition deal? Finance literature has much advances on this topic, but the results have not been conclusive. Bowers and Miller (1990) do not find a relationship between value creation for the bidder and the choice of using a first-tier investment banker. Servaes and Zenner (1996) find that the announcement returns for those firms hiring investment banks are lower than those do not. On the other hand, however, more recent literature find that the financial advisors do matter in an M&A or corporate takeover deal. Kale *et al.* (2003) document wealth gains to the bidder as the reputation of the bidder advisor increases relative to that of the target advisor. Bao and Edmans (2011) find a significant impact of the investment banks on M&A outcomes, contrasting earlier studies. Golubov *et al.* (2012) document a significantly higher bidder announcement return, higher success rate, and faster deal completion time that is associated with using a top-tier financial advisor in M&A deals when the target is a public company.

We build on the findings of Golubov *et al.* (2012) and examine the impact of financial advisors on M&A deals from the perspective of the social network, a topic that has been receiving increased attention in finance literature. Some literature find evidence showing that social ties have positive impact on M&A and IPO outcomes. Cai and Sevilir (2012), using a sample of U.S. M&As, document that the announcement returns are higher for those M&As where a common director is shared by the acquirer and target company. Renneboog and Zhao (2014), with a U.K. sample, report that the board connection between the acquirer and the target, measured as when there are one or more common directors exists, is associated with a higher likelihood of success takeover and shorter period of time for negotiation. They, however, do not find a significant impact of such connections on the announcement return. Cooney *et al.* (2015) find that when the directors and the executives of the underwriter and the IPO firm are connected through personal networks, the pre-IPO shareholders of the IPO firm are more likely to have a positive wealth gain, and the investment bank receives a higher compensation and a greater share allocation of the IPO firm, on average. Other literature document some negative or mixed impact of social networks on M&As and corporate governance. El-Khatib *et al.* (2015) find that bidder CEOs that are in a more central location of their personal connections are associated with more value losses to the acquirer and the combined business entity. Schmidt (2015) asserts that the social ties between CEO and the board can affect merger announcement return under different circumstances. He finds that when the value of board advice is high, the social ties are associated with a higher announcement return, but on the other hand, he finds that the social ties have a negative impact on acquirer performance, when the needs of high board monitoring outweighs the benefit from board advising.

The financial advisors in an M&A deal are expected to play a role of certification (Allen *et al.* 2004). More specifically, a financial advisor helps a buy-side client to collect information, evaluate a perspective target, perform due diligence, assess the value impact of the acquisition on the buy side, and negotiate and execute the deal if feasible. In other words, a deal should never be executed if it is deemed to be not value-creating to the bidder. We assert that the prior social connections between the senior executive members of the bidder and those of the financial advisor may impact the certification role of the financial advisor and thus affect the performance of an M&A deal. One the one hand, literature has find that social connections facilitate transmission of private information, business idea, and knowledge. For example, an extensive social network may facilitate the transmission of information among executives from different business organizations and thus may help firms to score better loan contracts (Engelberg *et al.* 2012), achieve better analyst performance (Cohen *et al.* 2010), improve portfolio management performance (Cohen *et al.* 2008), gain better M&A synergies (Cai & Sevilir 2012), and have a better overall corporate performance (Fracassi 2016).

On the other hand, however, social connections between the decision makers may interfere with optimal decision making, corporate governance, and value creating for the shareholders. For example, social ties among persons have been found to weaken the corporate governance and the monitoring effects on the managers (Fracassi & Tate 2012), to increase transaction costs (Cai *et al.* 2016), to encourage collusion among managers at the expenses of the shareholders (Ishii & Xuan 2014), and to have a worse IPO outcome (Jandik *et al.* 2016).

The question remains unanswered is how the social connections between the acquirer and their financial advisors affects the performance of an M&A deal. If the social connections between them help the financial advisors better learn the private information of the bidder firm, then such connections should help the financial advisor better certify and assess the deal, resulting in a better outcome. However, if such social connections encourage collusion between the bidder and the advisor, where nonprofitable deals are done, from which the advisors collect fees and CEO of the bidder firm enjoys a bigger power of governance and monetary incentives, then the shareholder’s value would be destroyed, and such deals would not be valued favorably by the financial market upon announcement.

We Use a sample of 675 M&A deals in the United States from 2000 to 2016 and use BoardEx to identify personal connections from prior common work experience in public and private firms between the CEO, CFO, COO, President and Chair of Board of the bidder firms and those of bidder firms’ financial advisors. Our results show that the announcement returns of the deals with personal connection between the bidders and their advisors are 1.59% lower than those of the deals where no such personal connection exist, which is a sizable difference given a -0.35% median bidder announcement CAR. However, choosing a financial advisor is affected by deal characteristics (Francis *et al.* 2014), and that which financial advisor to hire is a choice of the bidder firm, resulting in a potential selection bias (Golubov *et al.* 2012). Therefore, we consider the endogeneity issues in the matching of bidder and their advisor and control for the endogeneity by using the two-stage procedure proposed by Heckman (1979) and the switching regression model with endogenous switching, an extension of Heckman (1979) model used by Golubov *et al.* (2012). Our results show that, controlling for endogeneity, a bidder that personally connects to their financial advisor would have done a better deal if the financial advisor was not connected – or an 1.35% improvement in CAR. A non-connected bidder could have performed worse, had they connected to their financial advisor – a -3.11% change in CAR. We also use the propensity score matching proposed by Rosenbaum and Rubin (1983) to match each sample with bidder-bidder advisor connections to a sample without such connection but has the closest propensity of having so. The results show that the CAR of the sample with bidder-bidder financial advisor connection is 1.58% lower than their matched sample. To further solidify the exclusion of endogeneity, we add an additional variable, the number of professional associations in the headquarter county of the bidder, as a predictor of personal connections between the bidder and their financial advisors. The number of professional associations in the headquarter county of the bidder is significant in determining the personal connection, and the inverse mills ratios we derive from the first stage of the Heckman procedure are not significant in the second stage, nor are they significant in the switch regressions we subsequently perform. Thus, the negative relations between the personal connection and the announcement CAR we find are not likely due to the endogenous selection of the financial advisor by the bidder or due to the selection bias from the samples that we observe.

We then investigate how personal connections between bidder and bidder financial advisors affect the probability of completion of the deal and duration of time for deal completion. The results show that a personal connection between the bidder and bidder advisor is positively associated with the likelihood of deal completion, and that for those completed deals where the target is a public company, the duration between deal announcement and deal completion is 16.8% longer for those deals with bidder-bidder advisor connections. These results indicate that deals with bidder-bidder advisor connections are more likely to be taken into effective but are executed in a less efficient and timely manner.

We then further examine the possible channels that motivates the deals that are value-destroying to the bidder shareholders. The financial advisors receive substantial amount of fees from the M&A deals worldwide (Hunter & Jagtiani 2003; Golubov *et al.* 2012), and if a personal connection between the bidder and bidder financial advisor prompts collusion, then the financial advisors are likely to be paid more for advising the deal. Using data from 265 deals where the financial advisor fees are disclosed, we find that the unconditional mean for the advisor fees paid by the bidder is 25.87 million US dollars when the bidder and bidder advisor are personally connected, and 11.40 million when not connected. After controlling for financial advisor reputation, deal and firm characteristics, following Golubov *et al.* (2012), we, in a subsample of 121 deals with data availability, find that the fees paid by the bidders are 57.6% higher when personal connections between bidder and bidder-advisor exist than those fees when no personal connections exist, controlling for deal and firm characteristics. Our results provide evidence that the premium fees paid by the bidder are not due to the quality and the reputation of the financial advisor, nor due to the nature of the deal, but are due to the personal connections between the bidder and their advisors.

Lastly, we investigate the impact of the personal connections between bidder and bidder financial advisor and the cash bonus of the bidder CEO receives in the year the M&A deal completes. Literature has documented that the CEOs of the acquiring firm commonly receive incentives following a successful acquisition, and such incentives are almost all in the form of cash bonus (Grinstein & Hribar 2004). Following Ishii and Xuan (2014), we focus on the cash bonus that the CEOs of the acquiring companies receive in the year of merger completion. From the 350 deals where the cash bonus is paid to the CEO of the acquiring company in the year the deal successfully completes, we show that unconditionally, the

CEOs are paid 88.7% more cash bonus when there are personal connections between the bidder and bidder financial advisors than when there are no such conditions. The ratio reduces to 48.2% when we control for financial advisor reputation, deal characteristics, and firm financial of the year. Given an average of 1.87 billion U.S. dollar cash bonus, our finding translates into about 900 thousand dollars more cash bonus compensation for the CEOs when personal connections between the bidder and their financial advisor exists, which is substantial.

Our results are robust under various of alternative model specification and controls. First, one concern is that the significant results we find about the personal connections between the bidder and their advisor and the outcome of the M&A deals is due to the proximity of the bidder and their advisor, not their actual prior connections. Therefore, we always include the geographical difference between the bidder and their advisor in all models to directly control for that, and all our results hold. Second, given that Golubov *et al.* (2012) find that the reputation of the financial advisor matters in public deals, we include a dummy variable indicating whether a deal is advised by a top financial advisor or not, and also include public target dummy variable in our analysis. Our results still remain unchanged, and the interaction between the bidder-bidder financial advisor connection and the top financial advisor does not appear to be significant and affect our results. Third, our main results still hold if we either control for the fact whether the target hires a financial advisor, or whether the personal connections between the target and their financial advisor. Our results are also similar if we use different time window to estimate the CAR around the merger announcement, or if we use different measures to control for the bidder size (Moeller *et al.* 2004). Therefore, the results we find are not due to the geographical distance of the bidder and their advisors, the connections or hiring of target advisor, or the size effect of the bidder.

Our paper contributes to the literature in several ways. First, we extend the literature of social ties in finance and show the economic value of such connections. We show that the social ties of the senior executives with the financial advisors matter in the M&A context. Our results suggest that such connections are more detrimental than beneficial, which means they are more likely to help the executives and the financial advisors to score personal interests than earn economic benefits for the bidder shareholders. Second, we are the first to investigate how the social connections between bidder and their advisor may affect the outcome of M&A transactions. We add evidence to the M&A literature about social ties that the connections between bidder and their advisor diminish the certification effect of the advisor, resulting in more value-destroying deals. Lastly, we offer insights about how financial market perceives such personal connections between corporate major decision makers and find that these connections are perceived negatively by the market upon the announcement of the M&A deal.

The paper proceeds as follows. Section 2 describes the data, section 3 presents the empirical results, and section 4 concludes.

2. Data

2.1 Social Connection Data

We obtain the social connection data of the acquirers and their financial advisors from BoardEx through Wharton Research Data Services. BoardEx database records bilateral connections of the board members and senior executives of the firms all over the world. Those connections include overlapping private firms, public firms, government and military employment history, education, and social clubs. BoardEx also contains the demographical information of the individuals the database includes. In our paper, we consider the bidder firm is connected to their financial advisor if the CEO, CFO, COO, President, or the Chair of the Board[17] of either side has overlapped employment background in private or public firm prior to the announcement year of the M&A transaction with the CEO, CFO, COO, President, or the Chair of the Board of the other side. We only use the employment-based connection because such connections are believed to be most reliable and trackable. Other types of connections like education are

[17] Our results are similar if we only consider connections between CEO and CFO of the bidder and those of the financial advisor.

not reliable, considering the large enrollment of a public university[18], where two individuals graduating in the same year may not even have known each other throughout the 4 years of time attending the same university.

2.2 M&A and Firm Characteristics

We obtain M&A data from Tomson Reuters SDC Database with the announcement date from 2000 to 2016, both acquirer and target being a United States firm. We exclude liquidations, bankruptcy acquisition, going private, leverage buyout, privatization, restructuring and reverse takeover. We also ensure that the samples are either a merger (code "M" in SDC), or acquisition of majority interest (code "AM" in SDC). The deal should also have transaction value and payment methods non-missing. Additionally, we require the bidder has stock return data available from CRSP and financial data available from COMPUSTAT. We follow Golubov et al. (2012) and use SDC League Tables to identify the top 8 financial advisors[19] by the value of the deal they advised during our sample period.

We then merge the social connection data with the M&A data. We only keep those M&A deals that BoardEx has coverage for both acquirer firm and their financial advisors to ensure accuracy of our connection data. We also exclude those deals where no financial advisor is used for the acquirer side. Our final sample contains a total of 675 M&A deals. For the final sample, we use ExecuComp to collect the data of the cash bonus of the CEO in the year of the M&A deal completion. We also use the data[20] from Rupasingha et al. (2006) for the measure of social capital capacity. We use the number of establishments in professional organizations in the county of the acquirers' headquarters as an additional determinant of the connection between the acquirer and their advisor.

---

[18] It is common for some large public universities to consistently have enrollment of more than 50,000 in any given year in the most recent years. For example, Texas A&M University, the Ohio State University, Arizona State University, and University of Central Florida, according to Wikipedia (2018).
[19] The top 8 financial advisors are: JP Morgan, Goldman Sachs & Co, Bank of America Merrill Lynch, Morgan Stanley, Citi, Barclays, Credit Suisse Group, and Commerzbank AG.
[20] The data is available from the website of Northeast Regional Center for Rural Development of The Pennsylvania State University.

Table 1 Summary Statistics

This table reports the summary statistics of the key variables in the analysis. Bidder Connection to Advisor is a dummy variable that takes one if an employment-based personal connection between the CEO, CFO, COO, President and Chair of the Board exists between bidder and bidder financial advisor. Bidder CAR is the cumulative abnormal return of the bidding firm from 2 days prior to to 2 days after the announcement. Top Advisor Hired is a dummy variable that takes one if the financial advisor is one of the top 8 financial advisors according to the League Table. Deal Size to Total Assets is the deal value reported by SDC divided by the total assets of the firm in the year prior to the M&A announcement. Market Value is the stock price of the bidding firm 4 weeks prior to the announcement multiply by the number of shares outstanding. Market Adjusted Runups is the market-adjusted buy-and-hold return of the bidding firm stock from 205 days before to 6 days after the announcement. Sigma is the standard deviation of the daily stock return of the bidding firm from 205 days before to 6 days after the announcement. Cash Payment Used is a dummy variable that takes one if cash is used as a payment in the deal, and 0 otherwise. Tobin's Q is calculated as the sum of the market value of equity (price per share at the end of the fiscal year prior to the announcement multiply by the number of shares outstanding), total liability, and the liquidating value of preferred stock, all divided by the book value of the total assets. Leverage is the debt to asset ratio. Liquidity is the cash flows-to-equity ratio calculated as the Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the number of shares outstanding times the closing stock price at the fiscal year-end prior to the announcement. Same Industry Deal is a dummy variable that takes one if the bidder and the target are in the same industry based on two-digit SIC code. Tender Offer is a dummy variable that takes one if the offer is a tender offer reported by SDC. Target is Public is a dummy that takes one if the target firm is a listed company, and zero otherwise. Distance between Bidder and Advisor is the direct distance between the headquarters of the bidder and their advisor. Deal Completion is a dummy variable that takes one if the deal is eventually effective as shown in the SDC and zero otherwise. Bidder Advisor Fee is the fee paid to the bidder advisor reported by SDC. CEO Cash Bonus is the cash bonus received by the CEO of the bidder in the year the M&A deal completes. Days to Resolution if Success is the number of calendar days from the announcement date to the effective date for the deals bid by a listed firm.

	Unit	N	Mean	p10	p50	p90	Standard Deviation
Bidder Connection to Advisor	Binary	675	0.21	0.00	0.00	1.00	0.41
Bidder CAR		675	0.00	-0.09	0.00	0.09	0.08
Top Advisor Hired	Binary	675	0.62	0.00	1.00	1.00	0.49
Deal Size to Total Assets		675	2.03	0.02	0.19	0.91	34.11
Market Value	Billion $	675	22.09	0.64	4.65	64.04	48.54
Market Adjusted Runups		675	0.12	-0.25	0.05	0.46	0.51
Sigma		675	0.02	0.01	0.02	0.03	0.01
Cash Payment Used	Binary	675	0.83	0.00	1.00	1.00	0.38
ROA		675	0.06	0.00	0.06	0.14	0.09
Tobin's Q		675	2.25	1.08	1.74	3.79	2.09
Leverage		675	0.22	0.00	0.19	0.47	0.19
Liquidity		675	0.07	0.00	0.06	0.15	0.10
Same Industry Deal	Binary	675	0.67	0.00	1.00	1.00	0.47
Tender Offer	Binary	675	0.17	0.00	0.00	1.00	0.38
Target is Public	Binary	675	0.70	0.00	1.00	1.00	0.46

Table 1 Summary Statistics (Cont.)

	Unit	N	Mean	p10	p50	p90	Standard Deviation
Distance between Bidder and Advisor	Miles	675	932.10	19.78	706.10	2,461.00	874.90
Deal Completion	Binary	675	0.89	0.00	1	1	0.31
Bidder Advisor Fee	Million $	265	13.75	0.58	8.00	35.00	16.03
CEO Cash Bonus	Million $	350	1.91	0.18	1.05	5.00	2.86
Days to Resolution if Success		406	122.4	43	101	240	79.58

The summary statistics of our final sample is presented in Table 1. 21% of our sample has bidder-bidder financial advisor connections, and 62% of our sample have been advised by a top bidder financial advisor. The average direct distance between a typical bidder and their advisor is 932 miles. A typical deal in our sample as an announcement CAR of 0.04%, a deal value to total asset of 2.03, a market adjustment runup from 205 days to 6 days prior to the announcement of 11.65%, and a standard deviation of the daily stock return during the same period of 2.04%. 67% of the sample deals are same-industry deal where the bidder and the target are in the same industry, 17% of the deals are tender offers, 70% of the deals involve a public target, and 83% of the deals involve cash payment. A typical bidder in our sample has a total market value of 22.1 billion U.S. dollars, based on the stock price 4 weeks prior to the announcement date, a return on asset of 5.75%, a Tobin's Q of 2.25, a leverage of 0.22, and a cash flow to equity ratio of 6.97%, all based on the Compustat data in the year prior to the announcement year. Based on the SDC data availability, the bidder advisor fees are disclosed in 265 deals, of which the mean advisor fee is 13.75 million U.S. dollars. 350 CEOs are reported to have received cash bonus in the year the M&A deal is complete, and the mean bonus is 1.91 million U.S. dollars. It takes a typical deal with a public target 122 days to resolve, if the deal is eventually complete.

3. Empirical Results

3.1 Bidder-Bidder Financial Advisor Connections and Bidder CAR

We first examine how the connections between bidder and their advisor affect the announcement CAR of the bidder. According to the prior literature, we control for the deal and firm characteristics that have found to impact bidder announcement CAR. We control for the bidder size (Moeller et al. 2004), Tobin's q (Lang et al. 1989; Servaes 1991), leverage (Maloney et al. 1993; Billett et al. 2004), profitability (Lang et al. 1991), and cash flow to equity ratio (Jensen 1986; Lang et al. 1991; Smith & Kim 1994). We also control for bidder financial advisor reputation, which is related to the bidder CAR according to Golubov et al. (2012). The bidder size is measured as the market value of the bidder 4 weeks prior to the announcement date. The Tobin's q is measured as the sum of the book value of debt and market value of equity divided by total asset. The leverage is the total debt to total asset ratio. The profitability is the return on asset. The cash flow to equity ratio is measured as the income before extraordinary items plus depreciation minus dividends on common stock and preferred stock divided by the total market value of the equity at the fiscal year-end prior to the announcement. All these firm financial data is based on the fiscal year end immediately prior to the announcement year. We also control for the M&A deal related characteristics that may affect bidder CAR, which are relative deal size (Fuller et al. 2002), bidder stock run-ups (Rosen 2006), bidder stock return volatility (Moeller et al. 2007), cash payment being used (Travlos 1987), same-industry deal (Morck et al. 1990), tender offer (Jensen & Ruback 1983), and target firm being public (Golubov et al. 2012). Relative deal size is the natural logarithm of deal value to the bidder total assets. The bidder stock runups is the market adjust return of the bidder stock during 205 to 6 days prior to the announcement date. The bidder stock return volatility is the standard deviation of the daily stock return of the bidder during 205 to 6 days prior to the announcement date. The cash payment being used is a dummy that takes 1 if cash is used to pay for the acquisition and 0 otherwise. Same-industry deal is a dummy that takes 1 if the acquirer and the target are in the same industry, and 0 other wise. The target firm being public is a dummy that takes 1 if the target is a publicly traded firm and 0 otherwise.

Table 2 Bidder-bidder Advisor Connection and Bidder Announcement CAR

This table reports the results of the OLS regression of the bidder CAR (-2,2) around the announcement date. The dependent variable is the cumulative abnormal return of the bidding firm from 2 days prior to to 2 days after the announcement. Bidder Connection to Advisor is a dummy variable that takes one if an employment-based personal connection between the CEO, CFO, COO, President and Chair of the Board exists between bidder and bidder financial advisor. Top Advisor Hired is a dummy variable that takes one if the financial advisor is one of the top 8 financial advisors according to the League Table. Relative Deal Size is the natural logarithm of deal value reported by SDC divided by the total assets of the firm in the year prior to the M&A announcement. Bidder Size is the stock price of the bidding firm 4 weeks prior to the announcement multiply by the number of shares outstanding. Bidder Market Adjusted Runups is the market-adjusted buy-and-hold return of the bidding firm stock from 205 days before to 6 days after the announcement. Bidder Stock Return Volatility is the standard deviation of the daily stock return of the bidding firm from 205 days before to 6 days after the announcement. Cash Payment Used is a dummy variable that takes one if cash is used as a payment in the deal, and 0 otherwise. ROA is the return on assets of the bidder in the year prior to the announcement. Tobin's Q is calculated as the sum of the market value of equity (price per share at the end of the fiscal year prior to the announcement multiply by the number of shares outstanding), total liability, and the liquidating value of preferred stock, all divided by the book value of the total assets. Leverage is the debt to asset ratio. Cash Flow to Equity Ratio is the cash flows-to-equity ratio calculated as the Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the number of shares outstanding times the closing stock price at the fiscal year-end prior to the announcement. Same Industry Deal is a dummy variable that takes one if the bidder and the target are in the same industry based on two-digit SIC code. Tender Offer is a dummy variable that takes one if the offer is a tender offer reported by SDC. Target is Public is a dummy that takes one if the target firm is a listed company, and zero otherwise. Bidder-bidder Advisor Distance is the direct distance between the headquarters of the bidder and their advisor. All models include year and industry fixed effect. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable = CAR (-2, +2)	(1)	(2)	(3)
Bidder-bidder Advisor Connection	-0.0166**	-0.0164**	-0.0159**
	(0.00752)	(0.00757)	(0.00762)
Top Financial Advisor Dummy		-0.00153	0.000996
		(0.00782)	(0.00788)
Relative Deal Size	-0.00173	-0.00170	3.86e-05
	(0.00307)	(0.00310)	(0.00313)
Bidder Size	-1.10e-07**	-1.09e-07**	-7.81e-08
	(5.26e-08)	(5.29e-08)	(5.10e-08)
Bidder Market Adjusted Runups	-4.09e-05	-0.000116	-0.000791
	(0.0114)	(0.0114)	(0.0116)
Bidder Stock Return Volatility	0.127	0.119	-0.0756
	(0.471)	(0.471)	(0.476)
Cash Payment Used	0.0224**	0.0224**	0.0194**
	(0.00992)	(0.00992)	(0.00969)
ROA	0.0207	0.0212	0.0180
	(0.0615)	(0.0616)	(0.0599)

Table 2 Bidder-bidder Advisor Connection and Bidder Announcement CAR (Cont.)

Dependent variable = CAR (-2, +2)	(1)	(2)	(3)
Tobin's Q	-0.00228	-0.00225	-0.00238
	(0.00196)	(0.00198)	(0.00195)
Leverage	0.0329	0.0330	0.0325
	(0.0226)	(0.0227)	(0.0223)
Cash Flow to Equity Ratio	0.0543	0.0541	0.0529
	(0.0483)	(0.0483)	(0.0492)
Same Industry Deal	0.00679	0.00673	0.00869
	(0.00703)	(0.00704)	(0.00700)
Tender Offer	0.00405	0.00401	0.0140*
	(0.00778)	(0.00779)	(0.00837)
Target is Public			-0.0246***
			(0.00856)
Bidder-bidder Advisor Distance	-1.01e-06	-9.91e-07	-7.69e-08
	(4.22e-06)	(4.25e-06)	(4.24e-06)
Constant	-0.0632*	-0.0625*	-0.0560
	(0.0329)	(0.0322)	(0.0367)
Industry Dummy	Y	Y	Y
Year Dummy	Y	Y	Y
Observations	675	675	675
Adjusted R-squared	0.073	0.071	0.086

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The regression results are shown in Table 2. The dependent variable CAR (-2,2) is the cumulative abnormal return of the bidder from 2 days prior to the announcement date to 2 days after that. Year and industry fixed effect are included in all models, and the heteroskedastic-robust standard errors are reported in the parentheses. Column (1) presents our base model, where only the bidder financial characteristics and deal characteristics are included. The variable of interest is Bidder-bidder Advisor Connection, which is statistically significant and negative. This indicates that the existence of bidder-bidder financial advisor connection negatively impacts the bidder CAR. We add control for top financial advisor dummy in column (2) and target firm being public dummy in column (3), as Golubov et al. (2012) find that those two factors matter in bidder CAR. Our key variable, Bidder-bidder Advisor Connection, is still negatively significant with those two controls. The coefficient in the column (3) suggest that the connection between bidder and bidder financial advisor makes the bidder CAR 1.59% lower than if there was no connection exists. Other variables related to firm financial characteristics and deal characteristics are generally in the same directions as previous literature has predicted. Overall, our initial results indicate that the connection between bidder and their financial advisor has a negative impact on bidder CAR.

3.2 Determinants of Bidder-Bidder Financial Advisor Connection and Selection Bias Correction

Note that the results we find above assume that the connection between the bidder and their advisors are exogenously determined, which is plausible. In fact, such connection could also be determined endogenously by the firm characteristics and the deal characteristics. Furthermore, such connection can be affected by the availability of the financial advisor in the proximity of the bidder firm. If these suspicions hold true, there could be a selection bias exists, and the results we produce above could thus be unreliable, according to Heckman (1979). Therefore, we follow similar approach used by Golubov et al. (2012) using a two-step procedure to correct and control for the self-selection bias and endogeneity.

In the first step we implement a probit model that predicts the likelihood of a connection exists between the bidder and bidder financial advisor. In the second stage, we use the inverse mills ratio derived from the first stage to correct the selection bias. Li and Prabhala (2007) suggest that it is ideal to include a variable in the first stage, but the same variable does not appear in the second stage. In other words, that variable should have an impact on the likelihood of the existence of a bidder-bidder financial advisor connection but does not have an impact on the outcome of the M&A transaction. We therefore include the number of establishments in professional organizations in the county of the acquirers' headquarters as an additional determinant of the connection between the bidder and their advisor. We argue that more professional organizations in the county of the acquirer's headquarter offer greater opportunities for the firm's executive members to participate in more social events, engage in more business and employment activities, and thus increases the chance that they involve a financial advisor that they have connection with in the M&A deal. However, the number of professional organizations in an area is unlikely to affect the performance of the firm in the M&A transaction.

The column (1) of Table 3 reports the results of the probit model that estimates the likelihood of a connection between the bidder and their financial advisor. The Number of Professional Organizations variable is highly significant (at the 5% level), indicating the number of professional associations in the proximity of the headquarter of the bidder is positively related to the likelihood of the existence of bidder-bidder financial advisor connection. The relative deal size is negatively associated with the probability of hiring a connected financial advisor, implying that those deals that are more important to the bidder are less likely to involve a connected financial advisor, likely because the negative effect of hiring a connected financial advisor is easily to be noticed due to the relative size of the deal to the bidder. The bidder size is positively related to hiring a connected financial advisor, and the advisor being a top banker is also positively associated with the probability of being included as a connected financial advisor.

The columns (2) and (3) in Table 3 report the second stage of the Heckman procedure. In the second stage, we add an inverse Mills ratio, derived from the first stage of the Heckman procedure, as an additional independent variable. The column (2) represents the base model of our analysis, and the column (3) represents the model that includes the financial advisor reputation variable and the dummy indicating the target firm being public. The coefficients of the inverse Mills ratio in both models are not significant, indicating that there is no evidence of self-selection bias in our initial analysis. Nevertheless, we follow Golubov et al. (2012) and implement a switching regression approach with endogenous switching to estimate the effect of a connection between bidder and bidder financial advisor on the bidder CAR. More specifically, we examine what the CAR would have been, if the M&A deal, which actually has bidder-bidder financial advisor connection, had been announced without the existence of bidder-bidder financial advisor connection? Also, what the CAR could have been, if the deal without bidder-bidder financial advisor connection had been announced with a connection between bidder and bidder financial advisor? We answer these two what-if questions by estimating OLS models on bidder CAR on subsamples with and without bidder-bidder financial advisor connections, respectively, with the inverse Mills ratio we derived in the probit model described above included in all models. Table 4 Panel A reports the results of the switching regression models, and Panel B reports the results of the what-if analysis.

Table 3 Heckman Two-stage Regression for Bidder Announcement CAR

This table reports the Heckman (1979) two-stage regression for bidder announcement CAR. The dependent variable of the column (1) is a dummy that takes one if a bidder-financial advisor connection exists and zero otherwise. The column (1) is a probit model that predicts the likelihood of the completion of a deal. The columns (2) and (3) are OLS regression models. The dependent variables of the columns (2) and (3) are the bidder CAR (-2,2) around the announcement date. The Inverse Mills Ratio is derived using model (1) and is included in models (2) and (3). Top Advisor Hired is a dummy variable that takes one if the financial advisor is one of the top 8 financial advisors according to the League Table. Relative Deal Size is the natural logarithm of the deal value reported by SDC divided by the total assets of the firm in the year prior to the M&A announcement. Bidder Size is the stock price of the bidding firm 4 weeks prior to the announcement multiply by the number of shares outstanding. Bidder Market Adjusted Runups is the market-adjusted buy-and-hold return of the bidding firm stock from 205 days before to 6 days after the announcement. Bidder Stock Return Volatility is the standard deviation of the daily stock return of the bidding firm from 205 days before to 6 days after the announcement. Cash Payment Used is a dummy variable that takes one if cash is used as a payment in the deal, and 0 otherwise. ROA is the return on assets of the bidder in the year prior to the announcement. Tobin's Q is calculated as the sum of the market value of equity (price per share at the end of the fiscal year prior to the announcement multiply by the number of shares outstanding), total liability, and the liquidating value of preferred stock, all divided by the book value of the total assets. Leverage is the debt to asset ratio. Cash Flow to Equity Ratio is the cash flows-to-equity ratio calculated as the Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the number of shares outstanding times the closing stock price at the fiscal year-end prior to the announcement. Same Industry Deal is a dummy variable that takes one if the bidder and the target are in the same industry based on two-digit SIC code. Tender Offer is a dummy variable that takes one if the offer is a tender offer reported by SDC. Target is Public is a dummy that takes one if the target firm is a listed company, and zero otherwise. Bidder-bidder Advisor Distance is the direct distance between the headquarters of the bidder and their advisor. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable	(1) Prob(Connection Exists)	(2) CAR (-2, +2)	(3) CAR (-2, +2)
Inverse Mills Ratio		0.00476	-0.0285
		(0.0175)	(0.0339)
Top Financial Advisor Dummy	0.455***		-0.0112
	(0.133)		(0.0152)
Relative Deal Size	-0.127**	-0.00177	0.00371
	(0.0543)	(0.00346)	(0.00508)

Table 3 Heckman Two-stage Regression for Bidder Announcement CAR (Cont.)

Dependent Variable	(1) Prob(Connection Exists)	(2) CAR (-2, +2)	(3) CAR (-2, +2)
Bidder Size	3.87e-06***	-1.16e-07	-1.72e-07*
	(1.32e-06)	(7.18e-08)	(9.86e-08)
Bidder Market Adjusted Runups		-0.000475	-0.00122
		(0.0112)	(0.0116)
Bidder Stock Return Volatility		0.120	-0.0713
		(0.482)	(0.488)
Cash Payment Used	-0.150	0.0229**	0.0239**
	(0.167)	(0.0101)	(0.0105)
ROA	1.635	0.0264	-0.0233
	(1.000)	(0.0667)	(0.0736)
Tobin's Q	-0.125**	-0.00249	0.00117
	(0.0612)	(0.00261)	(0.00430)
Leverage	0.272	0.0325	0.0276
	(0.306)	(0.0231)	(0.0227)
Cash Flow to Equity Ratio	0.00735	0.0495	0.0509
	(0.593)	(0.0475)	(0.0482)
Same Industry Deal	-0.0278	0.00629	0.00852
	(0.123)	(0.00709)	(0.00707)
Tender Offer		0.00381	0.0137
		(0.00782)	(0.00844)
Bidder-bidder Advisor Distance		3.78e-07	1.49e-06
		(4.20e-06)	(4.24e-06)
Target is Public	0.0346		-0.0257***
	(0.131)		(0.00860)
Number of Professional Organizations	0.00183**		
	(0.000925)		
Constant	-0.884**	-0.0702*	-0.0218
	(0.390)	(0.0407)	(0.0556)
Industry Dummy	N	Y	Y
Year Dummy	Y	Y	Y
Observations	675	675	675
Pseudo R-squared/Adjusted R-squared	0.106	0.067	0.081

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 Switching Regression Model for Bidder Announcement CAR, What-if Analysis, and Propensity Score Matching

Table 4 reports the results of the switching regression model for bidder announcement CAR in Panel A, what-if analysis in Panel B, and propensity score matching in Panel C. The dependent variables in Panel A are bidder announcement CAR (-2,+2), where columns (1) and (2) are based on the subsample that a bidder-bidder financial advisor connection exists, and that columns (3) and (4) are based on the subsample that no such connection exists. The Inverse Mills Ratio is derived using model (1) in Table 3. Top Advisor Hired is a dummy variable that takes one if the financial advisor is one of the top 8 financial advisors according to the League Table. Relative Deal Size is the natural logarithm of the deal value reported by SDC divided by the total assets of the firm in the year prior to the M&A announcement. Bidder Size is the stock price of the bidding firm 4 weeks prior to the announcement multiply by the number of shares outstanding. Bidder Market Adjusted Runups is the market-adjusted buy-and-hold return of the bidding firm stock from 205 days before to 6 days after the announcement. Bidder Stock Return Volatility is the standard deviation of the daily stock return of the bidding firm from 205 days before to 6 days after the announcement. Cash Payment Used is a dummy variable that takes one if cash is used as a payment in the deal, and 0 otherwise. ROA is the return on assets of the bidder in the year prior to the announcement. Tobin's Q is calculated as the sum of the market value of equity (price per share at the end of the fiscal year prior to the announcement multiply by the number of shares outstanding), total liability, and the liquidating value of preferred stock, all divided by the book value of the total assets. Leverage is the debt to asset ratio. Cash Flow to Equity Ratio is the cash flows-to-equity ratio calculated as the Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the number of shares outstanding times the closing stock price at the fiscal year-end prior to the announcement. Same Industry Deal is a dummy variable that takes one if the bidder and the target are in the same industry based on two-digit SIC code. Tender Offer is a dummy variable that takes one if the offer is a tender offer reported by SDC. Target is Public is a dummy that takes one if the target firm is a listed company, and zero otherwise. Bidder-bidder Advisor Distance is the direct distance between the headquarters of the bidder and their advisor. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Switching Regression Model for Bidder Announcement CAR

Dependent variable = CAR (-2, +2)	(1)	(2)	(3)	(4)
	Connection Exists	Connection Exists	No Connection	No Connection
Inverse Mills Ratio	-0.0292	0.0365	0.00289	-0.0651
	(0.0433)	(0.106)	(0.0204)	(0.0411)
Top Financial Advisor Dummy		0.0413		-0.0274
		(0.0468)		(0.0184)
Relative Deal Size	0.00402	-0.000799	-0.00519	0.00413
	(0.00792)	(0.0114)	(0.00381)	(0.00572)
Bidder Size	-8.10e-08	1.28e-07	-1.59e-07	-3.19e-07**
	(1.87e-07)	(3.06e-07)	(9.75e-08)	(1.47e-07)
Bidder Market Adjusted Runups	-0.0358	-0.0290	0.000290	-0.00111
	(0.0358)	(0.0339)	(0.0130)	(0.0135)
Bidder Stock Return Volatility	0.126	-0.0615	0.361	0.246
	(1.335)	(1.352)	(0.532)	(0.534)

Table 4 Switching Regression Model for Bidder Announcement CAR, What-if Analysis, and Propensity Score Matching (Cont.)

Dependent variable = CAR (-2, +2)	(1)	(2)	(3)	(4)
	Connection Exists	Connection Exists	No Connection	No Connection
Cash Payment Used	0.0138	-0.00327	0.0229**	0.0284**
	(0.0228)	(0.0263)	(0.0116)	(0.0126)
ROA	-0.287*	-0.129	0.0404	-0.0575
	(0.157)	(0.155)	(0.0757)	(0.0854)
Tobin's Q	0.00242	-0.00477	-0.00264	0.00507
	(0.00742)	(0.0156)	(0.00302)	(0.00508)
Leverage	0.130	0.145	0.0165	0.00700
	(0.103)	(0.0913)	(0.0259)	(0.0256)
Cash Flow to Equity Ratio	-0.297***	-0.279***	0.109*	0.117*
	(0.0982)	(0.0940)	(0.0604)	(0.0609)
Same Industry Deal	0.0453***	0.0397***	-0.00296	0.000471
	(0.0134)	(0.0130)	(0.00845)	(0.00840)
Tender Offer	0.0239	0.0396*	0.00234	0.0112
	(0.0183)	(0.0207)	(0.00937)	(0.0102)
Bidder-bidder Advisor Distance	6.60e-06	1.08e-05	-2.16e-06	-1.22e-06
	(1.38e-05)	(1.43e-05)	(4.85e-06)	(4.86e-06)
Target is Public		-0.0456*		-0.0234**
		(0.0231)		(0.00958)
Constant	-0.0349	-0.120	-0.0506	0.0387
	(0.0999)	(0.165)	(0.0482)	(0.0660)
Industry Dummy	Y	Y	Y	Y
Year Dummy	Y	Y	Y	Y
Observations	142	142	533	533
Adjusted R-squared	0.196	0.251	0.065	0.078

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: What-if Analysis

	Connection Exists	No Connection
Actual CAR (1)	-1.043%	0.331%
Hypothetical CAR (2)	0.311%	-2.779%
Improvement ((1) – (2))	1.354%**	-3.109%***
N	142	533

Panel C: Propensity Score Matching Analysis

	Subsample that Connection Exists (1)	Matched Sample without Connection (2)
Actual CAR	-1.043%	0.536%
(1) – (2)	-1.579%**	
N	142	142

We show that the inverse Mills ratios are still insignificant in all subsample models presented in Panel A. We then compute the hypothetical CAR of those samples with bidder-bidder financial advisor connection by applying the coefficients of the “no connection” model to the actual data of the “connection exists" samples. Similarly, we compute the hypothetical CAR of those samples without bidder-bidder financial advisor connection by applying the coefficients of the "connection exists" model to the actual data of the "no connection" samples. The comparison between the actual CAR and the hypothetical CAR, as a what-if analysis using the models (2) and (4) in the Panel A of Table 4, is presented in the Panel B of Table 4[21]. We show that those M&A deals with connections between the bidder and bidder financial advisor would have improve the announcement CAR by 1.35%, if there is no such connection exists. On the other hand, the M&A deals announced without a bidder-bidder financial advisor connection would have been worsened by 3.11% in terms of the announcement CAR had they chosen a connected financial advisor. Both numbers are statistically and economically significant, given an average (median) CAR of 0.04% (-0.35%).

Furthermore, we implement the propensity score matching technique proposed by Rosenbaum and Rubin (1983) to match each M&A deal that involves a connected financial advisor with one that does not by the closest probability of involving a connected financial advisor. The probability of involving a connected financial advisor is estimated using the same probit model presented in Table 3 column (1). We then compare the actual CAR of the subsample that a connection exists with the actual CAR of the matched sample without connections. The results are shown in Table 4 Panel C. We show that the CAR of the "connection exists" sample is 1.58% lower than that of the matched sample. The difference is statistically significant at the 5% level.

Overall, we present evidence showing that involving a financial advisor whose top executive leaders have prior employment connections with those of the bidder has a significant negative impact on the bidder CAR, and that such impact is statistically and economically meaningful, which is unlikely to be caused by self-selection bias.

[21] The comparison using the models in column (1) and (3) of Table 4 Panel A yields similar magnitudes and significance.

3.3 Bidder-bidder Advisor Connection and Deal Completion

We then investigate if the connection between bidder and bidder advisor helps the bidder to score a higher odd of complete the deal. Particularly, using a probit model, we estimate the probability of a deal completion on the connection between bidder and bidder advisor, bidder characteristics, and deal characteristics. We construct the model following Golubov et al. (2012) and El-Khatib et al. (2015), and the results are shown in Table 5. Consistent with prior literature, high profitability, growth opportunity and low leverage bidders are more likely to complete the deal. In model (1), we show that bidder-bidder financial advisor connections has a positive impact on the likelihood of completing a deal, and that deal size to total assets ratio also has a positive impact, which is different from Golubov et al. (2012). Hence, we add an interaction term between bidder-bidder advisor connection and the deal size to total assets ratio in model (2). The coefficient shows a significant negative impact of the interaction term[22]. These results indicate that while a connection between bidder and bidder financial advisor may positively impact the likelihood of a deal completion, such impact is reduced, when the deal is relatively larger and thus more important to the bidder, or the bidder is a larger firm. This is consistent with the reputation effect of the social network argued by Jandik et al. (2016) that as the M&A deal becomes more noticeable, the influence of the personal connection between the bidder and their financial advisor on the deal, especially when a deal may more likely to be value destroying as we find in the previous section, is diminished.

[22] We obtain similar results of negative impact of the interaction term when interacting the deal size to total assets with the bidder size.

Table 5 Bidder-bidder Advisor Connection and Deal Completion

Table 5 reports the result of the probit model that predicts the likelihood of a deal completion. The dependent variables are the dummy variables that take one if a deal is eventually effective as recorded by SDC, and zero otherwise. Bidder-bidder Advisor Connection is a dummy variable that takes one if an employment-based personal connection between the CEO, CFO, COO, President and Chair of the Board exists between bidder and bidder financial advisor. Deal Size to Total Assets is the deal value reported by SDC divided by the total assets of the firm in the year prior to the M&A announcement. Top Advisor Hired is a dummy variable that takes one if the financial advisor is one of the top 8 financial advisors according to the League Table. Bidder Size is the stock price of the bidding firm 4 weeks prior to the announcement multiply by the number of shares outstanding. Bidder Market Adjusted Runups is the market-adjusted buy-and-hold return of the bidding firm stock from 205 days before to 6 days after the announcement. Bidder Stock Return Volatility is the standard deviation of the daily stock return of the bidding firm from 205 days before to 6 days after the announcement. Cash Payment Used is a dummy variable that takes one if cash is used as a payment in the deal, and 0 otherwise. ROA is the return on assets of the bidder in the year prior to the announcement. Tobin's Q is calculated as the sum of the market value of equity (price per share at the end of the fiscal year prior to the announcement multiply by the number of shares outstanding), total liability, and the liquidating value of preferred stock, all divided by the book value of the total assets. Leverage is the debt to asset ratio. Cash Flow to Equity Ratio is the cash flows-to-equity ratio calculated as the Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the number of shares outstanding times the closing stock price at the fiscal year-end prior to the announcement. Same Industry Deal is a dummy variable that takes one if the bidder and the target are in the same industry based on two-digit SIC code. Tender Offer is a dummy variable that takes one if the offer is a tender offer reported by SDC. Bidder-bidder Advisor Distance is the direct distance between the headquarters of the bidder and their advisor. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent variable = Prob (Deal Completion)	(1)	(2)
Bidder-bidder Advisor Connection	0.323*	0.648***
	(0.179)	(0.218)
Deal Size to Total Assets	0.00205*	0.00223*
	(0.00121)	(0.00130)
Bidder-bidder Advisor Connection* Deal Size to Total Assets		-0.760***
		(0.283)
Top Advisor Hired	0.00685	0.0254
	(0.149)	(0.151)
Bidder Size	-3.06e-06**	-3.31e-06***
	(1.20e-06)	(1.22e-06)
Bidder Market Adjusted Runups	0.0838	0.0799
	(0.133)	(0.131)
Bidder Stock Return Volatility	3.526	4.732
	(6.800)	(7.014)
Cash Payment Used	0.307	0.300
	(0.187)	(0.187)
ROA	2.323***	2.419***
	(0.848)	(0.867)

Table 5 Bidder-bidder Advisor Connection and Deal Completion (Cont.)

Dependent variable = Prob (Deal Completion)	(1)	(2)
Tobin's Q	0.0695	0.0694
	(0.0433)	(0.0426)
Leverage	-0.355	-0.344
	(0.388)	(0.393)
Cash Flow to Equity Ratio	-0.485	-0.430
	(0.735)	(0.755)
Same Industry Deal	0.115	0.150
	(0.139)	(0.141)
Tender Offer	-0.185	-0.199
	(0.186)	(0.189)
Bidder-bidder Advisor Distance	-8.14e-05	-9.09e-05
	(8.30e-05)	(8.38e-05)
Constant	0.819*	0.744*
	(0.431)	(0.440)
Industry Dummy	N	N
Year Dummy	Y	Y
Observations	675	675
Pseudo R-squared	0.0901	0.101

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.4 Bidder-bidder Advisor Connection and Deal Resolution Time

In this section, we examine whether a connection between the bidder and bidder advisor may shorten or lengthen the time from deal announcement to deal being effective. We are interested in this question because if a connection between the bidder and bidder financial advisor may facilitate the information transmission, a deal should be resolved faster, exhibiting a high efficiency of the deal execution. Golubov et al. (2012) argue that a shorter time between the deal announcement and deal resolution indicates the "skill effect" of a reputable financial advisor. In fact, they find that deals worked by reputable financial advisors indeed take a shorter time to resolve, consistent with their expected skill and efficiency. Therefore, we control for the top financial advisor in our analysis. Officer et al. (2009) argue that the resolution time for M&A deals is less important to consider when target is a private firm because private target deals are typically announced when done. Therefore, we only use the observations where the target firm is a public firm and the deal is finally completed in this analysis. The results of the OLS estimation is reported in Table 6.

Table 6 Bidder-bidder Advisor Connection and Time to Resolution

This table reports the OLS regression of the time to resolution on bidder-bidder advisor connection and other control variables. The dependent variables are the natural logarithm of number of days from the announcement day to the day that the deal is effective as reported by SDC database. Bidder-bidder Advisor Connection is a dummy variable that takes one if an employment-based personal connection between the CEO, CFO, COO, President and Chair of the Board exists between bidder and bidder financial advisor. Relative Deal Size is the natural logarithm of the deal value reported by SDC divided by the total assets of the firm in the year prior to the M&A announcement. Top Advisor Hired is a dummy variable that takes one if the financial advisor is one of the top 8 financial advisors according to the League Table. Bidder Size is the stock price of the bidding firm 4 weeks prior to the announcement multiply by the number of shares outstanding. Bidder Market Adjusted Runups is the market-adjusted buy-and-hold return of the bidding firm stock from 205 days before to 6 days after the announcement. Bidder Stock Return Volatility is the standard deviation of the daily stock return of the bidding firm from 205 days before to 6 days after the announcement. Cash Payment Used is a dummy variable that takes one if cash is used as a payment in the deal, and 0 otherwise. ROA is the return on assets of the bidder in the year prior to the announcement. Tobin's Q is calculated as the sum of the market value of equity (price per share at the end of the fiscal year prior to the announcement multiply by the number of shares outstanding), total liability, and the liquidating value of preferred stock, all divided by the book value of the total assets. Leverage is the debt to asset ratio. Cash Flow to Equity Ratio is the cash flows-to-equity ratio calculated as the Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the number of shares outstanding times the closing stock price at the fiscal year-end prior to the announcement. Same Industry Deal is a dummy variable that takes one if the bidder and the target are in the same industry based on two-digit SIC code. Tender Offer is a dummy variable that takes one if the offer is a tender offer reported by SDC. Bidder-bidder Advisor Distance is the direct distance between the headquarters of the bidder and their advisor. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable = Ln(Days to Resolution)	(1)	(2)	(3)
Bidder-bidder Advisor Connection	0.186***	0.187***	0.168***
	(0.0705)	(0.0711)	(0.0615)
Top Advisor Hired		-0.00432	-0.0730
		(0.0628)	(0.0594)
Relative Deal Size			0.143***
			(0.0297)
Bidder Size			2.79e-06***
			(5.67e-07)
Bidder Market Adjusted Runups			0.0229
			(0.0766)
Bidder Stock Return Volatility			-1.178
			(3.901)

Table 6 Bidder-bidder Advisor Connection and Time to Resolution (Cont.)

Dependent Variable = Ln(Days to Resolution)	(1)	(2)	(3)
Cash Payment Used			-0.0205
			(0.0654)
ROA			0.280
			(0.367)
Tobin's Q			-0.00992
			(0.0184)
Leverage			0.220
			(0.153)
Cash Flow to Equity Ratio			-0.0213
			(0.277)
Same Industry Deal			0.105**
			(0.0526)
Tender Offer			-0.544***
			(0.0657)
Bidder-bidder Advisor Distance			-2.50e-05
			(2.83e-05)
Constant	4.593***	4.595***	4.386***
	(0.0332)	(0.0519)	(0.176)
Industry Dummy	N	N	N
Year Dummy	Y	Y	Y
Observations	406	406	406
Adjusted R-squared	0.015	0.013	0.341

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is log of resolution days between announcement and taking into effect. Column (1) of Table 6 reports the unconditional impact of bidder-bidder advisor connection on resolution time and shows that a connection is associated with a longer time to resolution. In column (2), we add control for top financial advisors, and in column (3) additional controls for firm and deal characteristics. We show that the connection between bidder and bidder advisor is consistently positively significant. The coefficient of top advisor is negative, which is consistent with Golubov et al. (2012), but not significant. Based on the model in column (3), we find that all else equal, a deal will take 16.8% longer time to resolve, if a connection between bidder and bidder financial advisor exists[23], which is both statistically and economically significant. Overall, we find evidence showing that the deals advised by financial advisor with personal connections to the bidder take a longer time to resolve, controlling for advisor reputation, firm and deal characteristics. This implies that instead of utilizing the better information transmission benefited from personal connections, those connected financial advisors work inefficiently in those M&A deals in terms of the time to resolution.

3.5 Bidder-bidder Advisor Connection, Advisor Fees, and CEO Bonus

Given the results discussed above, we have shown that a personal connection between the bidder and their financial advisor is detrimental. It causes value loss to the shareholder at the M&A deal announcement, takes longer time to resolve, but has a higher likelihood to complete. It is therefore interesting to examine the motivation behind that, and study how the both sides of the connection benefit from the deal. Hence, we investigate whether the financial advisors are paid more fees, and the bidder CEOs are paid more bonus because of the personal connection between bidder and bidder financial advisor.

Corporates pay substantial amount of fees to their advisors, but such fees are not required by SEC to be disclosed in a M&A deals. As a result, we present the OLS regression model that estimates the advisor fees based on the 265 deals for which the advisor fee information is available in SDC database and bidder-bidder financial advisor connection information is available in BoardEx database. Table 7 shows the results. Model (1) shows the unconditional regression of log of advisor fees on the connection between bidder and their financial advisor. The coefficient is positive and statistically significant. In Model (2), we add a control variable for top advisors, which has a positive and significant coefficient, consistent with Golubov et al. (2012). The coefficient of bidder-bidder financial advisor connection is still positively significant. In Model (3), on top of the bidder-bidder financial advisor connection and top

[23] In unreported results, we find that all else equal, a deal takes 18.1 more days to resolve if there is a connection between bidder and bidder financial advisor, compared to one that with no such connection exists.

advisors, we control for firm and deal characteristics that will affect advisor fees following prior literature. The bidder-bidder financial advisor connection is still positive and statistically significant. Our results are also economically significant. Controlling for deal and firm characteristics, the financial advisors with personal connection to the bidder are paid 57.6% higher than those without a personal connection, which is substantial, considering the median payment to the advisor in our sample being 8 million U.S. dollars[24].

Table 7 Bidder-bidder Advisor Connection and Advisor Fees

This table reports the results of the OLS regression of the bidder financial advisor fees on the bidder-financial advisor connection and other control variables. The dependent variables are the natural logarithm of advisor fees paid to bidder financial advisor as reported by SDC database. Bidder-bidder Advisor Connection is a dummy variable that takes one if an employment-based personal connection between the CEO, CFO, COO, President and Chair of the Board exists between bidder and bidder financial advisor. Top Advisor Hired is a dummy variable that takes one if the financial advisor is one of the top 8 financial advisors according to the League Table. Deal size is the deal value recorded by SDC database. Relative Deal Size is the natural logarithm of the deal value reported by SDC divided by the total assets of the firm in the year prior to the M&A announcement. Cash Payment Used is a dummy variable that takes one if cash is used as a payment in the deal, and 0 otherwise. ROA is the return on assets of the bidder in the year prior to the announcement. Same Industry Deal is a dummy variable that takes one if the bidder and the target are in the same industry based on two-digit SIC code. Tender Offer is a dummy variable that takes one if the offer is a tender offer reported by SDC. Bidder Market Adjusted Runups is the market-adjusted buy-and-hold return of the bidding firm stock from 205 days before to 6 days after the announcement. Bidder Stock Return Volatility is the standard deviation of the daily stock return of the bidding firm from 205 days before to 6 days after the announcement. Distance between Bidder and Advisor is the direct distance between the headquarters of the bidder and their advisor. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable = ln(Advisor Fees)	(1)	(2)	(3)
Bidder-bidder Advisor Connection	1.224***	0.922***	0.576**
	(0.184)	(0.183)	(0.287)
Top Financial Advisor Dummy		1.508***	0.957***
		(0.165)	(0.295)
Deal Size			1.96e-05**
			(8.10e-06)
Relative Deal Size			0.271**
			(0.104)

[24] In unreported analysis, using raw advisor fees as dependent variable, and find that the financial advisors with personal connections to the bidder are, on average, paid 10.3 million dollars more than those without personal connections, controlling for deal and firm financial characteristics.

Table 7 Bidder-bidder Advisor Connection and Advisor Fees (Cont.)

Dependent Variable = ln(Advisor Fees)	(1)	(2)	(3)
Cash Payment Used			-0.0213
			(0.262)
Same Industry Deal			0.0263
			(0.244)
Tender Offer			-0.174
			(0.616)
Bidder Market Adjusted Runups			-0.259
			(0.277)
Bidder Stock Return Volatility			-28.67**
			(10.97)
Bidder-bidder Advisor Distance			1.00e-05
			(0.000122)
Constant	8.523***	7.667***	7.513***
	(0.102)	(0.142)	(0.581)
Observations	265	265	121
Adjusted R-squared	0.086	0.319	0.396

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

CEOs usually get cash bonus as a monetary incentive following a successful M&A deal (Grinstein & Hribar 2004). We follow Ishii and Xuan (2014) and therefore focus on the cash bonus that the CEOs of the bidding firm receive in the year that the M&A deal completes. Using the 350 M&A deals that finally complete and report a non-zero CEO bonus in the deal completion year, we implement OLS regression of the log of CEO cash bonus on the connection between bidder and bidder financial advisor. Unlike in previous analysis where firm financials are lagged one year, we use the same year firm financial characteristics in this analysis. The OLS regression results are shown in Table 8. We show the unconditional model in column (1) and control for the top financial advisor in model (2), where the bidder-bidder financial advisor connection is positive and highly significant in both models. In model (3) we add additional deal and firm financial characteristics, and in model (4) we add the stock return and volatility. The results show that the bidder-bidder advisor connection is consistently positive and significant in predicting CEO bonus. High stock return, larger firms, low stock volatility are also associated with higher CEO bonus, which is consistent with prior literature. Our results are economically significant as well. The CEOs in the firms where executive leaderships have personal connections to the financial advisors get paid 41.4% more in cash bonus, on average, in the acquisition completion year than those in the firms without such personal connections[25].

Table 8 Bidder-bidder Advisor Connection and CEO Bonus

This table reports the results of the OLS regression of CEO bonus on the bidder-bidder financial advisor connection and other control variables. The dependent variable is the natural logarithm of the bidding firm's CEO cash bonus in the year the deal is complete. Bidder-bidder Advisor Connection is a dummy variable that takes one if an employment-based personal connection between the CEO, CFO, COO, President and Chair of the Board exists between bidder and bidder financial advisor. Top Advisor Hired is a dummy variable that takes one if the financial advisor is one of the top 8 financial advisors according to the League Table. Total assets is the book value of total assets of the firm. Tobin's Q is calculated as the sum of the market value of equity (price per share at the end of the fiscal year prior to the announcement multiply by the number of shares outstanding), total liability, and the liquidating value of preferred stock, all divided by the book value of the total assets. Leverage is the debt to asset ratio. Cash Flow to Equity Ratio is the cash flows-to-equity ratio calculated as the Income before extraordinary items plus depreciation minus dividends on common and preferred stock divided by the number of shares outstanding times the closing stock price at the fiscal year-end prior to the announcement. All firm financial data are at the end of the fiscal year that the deal completes. Tender Offer is a dummy variable that takes one if the offer is a tender offer reported by SDC. Bidder-bidder Advisor Distance is the direct distance between the headquarters of the bidder and their advisor. Annual Stock Return is the buy-and-hold stock return of the firm in the current fiscal year. Stock Return volatility is the standard deviation of the daily stock return of the firm in the current fiscal year. Robust standard errors correcting heteroscedasticity are reported in the parentheses. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable = ln(CEO Cash Bonus)	(1)	(2)	(3)	(4)
Bidder-bidder Advisor Connection	0.887***	0.877***	0.476**	0.414*
	(0.199)	(0.202)	(0.222)	(0.218)
Top Financial Advisor Dummy		0.0731	0.138	0.00773
		(0.159)	(0.178)	(0.177)
Total Assets			2.28e-06***	4.53e-06***
			(4.85e-07)	(1.26e-06)
Tobin's Q			0.0393	0.0339
			(0.0369)	(0.0358)
Leverage			0.489	-0.422
			(0.498)	(0.543)
Cash Flow to Equity Ratio			0.187	-0.264
			(0.966)	(0.768)

[25] In unreported analysis using raw cash bonus as dependent variable, we find that CEO cash bonus is 0.89 million dollars higher when the deal involves a personally connected financial advisor, controlling for firm financial and deal characteristics.

Table 8 Bidder-bidder Advisor Connection and CEO Bonus (Cont.)

Dependent Variable = ln(CEO Cash Bonus)	(1)	(2)	(3)	(4)
Tender Offer			0.347*	0.364**
			(0.192)	(0.173)
Bidder-bidder Advisor Distance			-5.19e-05	0.000144
			(0.000117)	(0.000102)
Annual Stock Return				0.486**
				(0.236)
Stock Return Volatility				-59.66***
				(10.72)
Constant	6.586***	6.548***	6.418***	8.527***
	(0.0884)	(0.103)	(0.268)	(0.473)
Industry Dummy	N	N	N	N
Year Dummy	N	N	Y	Y
Observations	350	350	304	264
Adjusted R-squared	0.053	0.051	0.160	0.312

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Admittedly, due to the data availability, we are unable to observe the complete picture of financial advisor fees and the CEO cash bonus compensation. Nevertheless, based on the observable samples, we show evidence that the financial advisor and the CEO of the bidding firm get higher benefit in the forms of advisor fees and cash bonus, respectively, following a M&A deal when there are personal connections between the bidder and bidder financial advisor. This evidence sheds light on the motivation of those M&A deals carried out by connected bidders and their advisors. They are possibly utilizing the personal connections to collude and benefit each other at the expenses of the shareholders.

3.6 Additional Robustness Checks

One possible concern regarding the results of our analysis is that it may be the geographical distance between the bidder and bidder advisor, instead of the personal connection between the two firms, that affects the outcome of the M&A deal, as geographically closer bidder and financial advisors have a better chance to transmit information. Therefore, we control for the geographical distance between bidder and bidder financial advisor in all of our analysis. Our results are robust with these controls. Second, we control for the reputation effects by including a dummy indicating whether the financial advisor is one of the top 8 financial advisors ranked by the SDC League Table. Additionally, in unreported analysis, we add the interaction between the bidder-bidder financial advisor connection and the top financial advisor as an additional variable. Our results do not change, and the interaction effect is not significant. Third, in unreported analysis, we control for whether the target hires a financial advisor, and whether the target has a connection to their financial advisor. Our results still hold with these controls. Forth, we use an alternative measure, social capital index, which uses principle component analysis to measure the social capital intensity of an area considering all business and nonbusiness associations, as a determinant to estimate the likelihood of a connection between bidder and bidder financial advisor exists. Our results still hold. Additionally, we obtain similar results if using different time window to estimate the CAR, or if using different measure for bidder size.

4. Conclusion

The financial advisors have been playing a crucial rule in M&A deals, which are some of the most decisions a company makes. We extend the literature in understanding the rules and impact of a chosen financial advisor could have on the outcome of M&A deals and extend the understand of the social networks in finance. Using a sample of 675 M&A deals from 2000 to 2016 and the BoardEx database recording the personal work-related connections of millions of corporate decision makers in the world, we show that the existence of a connection between the top executives of the bidder and those of their financial advisors causes a lower announcement CAR. Such impact is not a result of the endogenous determinants of which financial advisor to hire. Using a Heckman two-stage procedure and switching regression with endogenous switches, we show that a typical M&A deal with personal connections between bidder and financial advisor could have had a 1.35% higher CAR if it was a deal without such connection exists. We also show that M&A deals advised by financial advisors that are personally connected to the bidder are more likely to complete, but it takes a longer time to resolve than deals without such connections. Our evidence indicates the detrimental effects of the personal connections between bidder and bidder financial advisors. We also investigate the motivation behind such behavior and phenomenon and find that the financial advisors are paid more fees for the advising services and the CEOs of the bidder companies are paid a higher cash bonus following a successful merger. These evidences imply that the both sides of the connection are pursuing personal interests at the expenses of shareholders in terms of a value loss at the announcement and less efficient and timely in processing the deal.

Our paper has several contributions to the literature. We extend the literature of social ties in finance and show the economic value of such connections. We are the first to investigate the impact of personal social ties between bidder and financial advisor under the context of M&A. We extend the literature in the financial advisor and M&A performance by showing that such social ties as bidder-bidder financial advisor are more detrimental than beneficial and diminishes the certification role of the financial advisors. Last but not the least, we offer insights about how financial market perceives such personal connections between bidder and bidder financial advisor and show that these connections are perceived negatively by the market upon the announcement of the M&A deal.

Chapter 3

Wealth Inequality, Leveraged Bubbles, and the Joneses Effect

1. Introduction

In recent decades, asset bubbles have become more frequent in the wealthiest nations. Jorda, Schularick, & Taylor (2015) document 139 equity and housing bubbles across 17 countries between 1870 and 2013, 97 (70%) of which occurred in the post-WWII era. They show that leveraged bubbles—those where assets such as real estate are financed by a high proportion of debt—often accompany financial crises and are especially damaging to economies when the bubbles burst.

Income and wealth inequality have also increased significantly over the last several decades. Using data primarily from the Federal Reserve Survey of Consumer Finances, Wolff (2016) shows that between 1962 and 2014, the share of income and wealth held by the top 5% of U.S. households increased 10 and 17 percentage points, respectively. Saez and Zucman (2016) use more detailed tax records to assess wealth at the very top of the distribution. They find that U.S. wealth concentration among the top 0.1% of families increased dramatically from 7% in 1978 to 22% in 2012, making wealth inequality is comparable to that of the early 20th century. In contrast, the wealth share of the bottom 90% of taxpayers plummeted since the mid-1980s mainly because middle-class savings plummeted. (Saez and Zucman, 2016) At the same time, the debt burdens of middle class households increased dramatically. The mean debt to income ratio of the middle three quartiles of households increased from 67% to 125% between 1983 and 2013, while the mean debt to net worth ratio increased from 37% to 64%. (Wolff, 2016)

Researchers have begun to explore theoretical and empirical connections between inequality and the build-up of leveraged bubbles. Rajan (2010) argues that wealth inequality was an underlying cause of the recent subprime financial crisis because low- and middle-income households increasingly accumulated debt to maintain or increase consumption, which left them prone to over-indebtedness and default on credit cards, housing, and auto loans.

An important question is *why* households felt the need to maintain or increase consumption beyond their earnings. In a survey of the literature connecting income inequality and financial crises, van Treeck (2014) distinguishes credit supply effects from credit demand effects. The credit supply story is that growing wealth inequality facilitated easy access to credit to low-income households. Rajan (2010) argues that government programs such as tax credits and Government Sponsored Enterprise housing affordability goals postpone the political pressure on the government to address the financial stress felt by most households. Kumhof et al. (2015) develop a dynamic stochastic general equilibrium (DSGE) model in which a crisis is driven by a permanent shift in income inequality because top earners use a large share of their higher income to accumulate financial wealth in the form of loans to bottom earners, who eventually default as relief from the high debt load outweighs the costs from default. Demarzo et al. (2008) present an overlapping generations model where agents' utilities depend on the wealth of their cohort, which induces relative wealth concerns. To avoid a relatively low-wealth outcome, agents herd into risky securities, which drives down their expected return. Even though the bubble is likely to burst and lead to a substantial loss, agents' relative wealth concerns make them afraid to trade against the crowd. With each of these explanations, the political or financial system endogenously facilitates the credit transfer to meet the desire of the wealthy to increase saving.

On the credit demand side, the neoclassical permanent consumption hypothesis could potentially explain the increase in household credit because it allows for intertemporal consumption smoothing for transitory, but only for transitory income shocks. The empirical evidence, however, shows that the decline in income for many households was permanent; the variance of transitory earnings declined or remained constant after the 1980s, providing little incentive for households to increase borrowing thereafter. (van Treeck, 2014) Alternatively, the relative income hypothesis states that a household's saving rate is an increasing function of (i) the household's position in the income distribution within its local reference group and (ii) the relation of the household's current to past income. (van Treeck, 2014) The first condition is the "keeping up with the Joneses" effect because the desire to consume increases with the household's perception of relative status in its local group. The second condition is consistent with habit persistence and the anchoring bias where an individual uses an incomplete reference point (e.g. last year's income) to make decisions about future consumption. The surge in income and wealth among the top 0.1% of taxpayers can lead to 'expenditure cascades' all the way down the income ladder if individuals are influenced by the spending patterns of others just above them in the income distribution (Frank et al., 2010). In addition, evidence from SCF shows that all households except the top 10% have become more strongly indebted since the late 1980s.

In sum, wealth inequality may facilitate leveraged bubbles if it leads to status-driven, debt-financed asset purchases by low- and middle-income households. These conditions plausibly existed in the U.S. during the subprime housing boom between 2000 and 2006. As home prices began to rise briskly, many households viewed a home purchase as a good investment because the momentum model suggested that homes would continue to appreciate. The benefits to homeownership spread by "psychological contagion" (Shiller, 2002) among friends, family, and neighbors. Households sought to improve their social status by becoming first-time homeowners, upscaling to more expensive homes, or tapping their home equity to purchase other durables. Financial intermediaries facilitated the credit demand through large-scale subprime securitization. (Mian and Sufi, 2009; Nadauld and Sherlund, 2013). The combination of these factors surely contributed to the financial crisis and Great Recession.

In this paper, we examine the effects of wealth inequality and social status on asset bubbles in an experimental lab setting. The treatments that we impose on traders mimic, to some degree, incentives that many households faced in deciding whether to purchase or refinance a house during the housing boom. To our knowledge, we are the first to use an experimental methodology to study the effect of wealth inequality, and the joint effects of inequality, leverage, and status on asset bubbles. Our experimental design is modeled after Smith, Suchanek, and Williams (1988; hereafter, SSW) and proceeds in three stages. Each stage consists of six sessions with a base group of six inexperienced traders with equal initial endowments, and a similar treatment group with unequal endowments where three randomly chosen traders are "rich" and three are "poor." The aggregate endowments of the equal and unequal sessions are always identical. The second and third stages introduce leverage and status, respectively, in addition to unequal endowments.

The first stage examines the effect of equal versus unequal initial endowments. Experimental researchers have shown that momentum trading models explain asset price paths quite well. (Caginalp et al., 2000a; Caginalp et al., 2000b) Traders with unequal endowments, however, may produce different momentum dynamics than traders with equal endowments. On the one hand, the concentrated liquidity among the rich traders may lead to greater momentum effects if they primarily trade with one another. On the other hand, poor traders are less able to contribute to an emerging bubble because they are liquidity constrained. The ultimate outcome may depend on the cognitive skills and degree of risk aversion of the rich and poor traders.

The second stage introduces leverage where traders in both the equal and unequal endowment sessions can borrow interest-free from the experimenter up to 75% of the market value of their asset holdings. This condition simulates the high leverage of home financing. Experimental research has convincingly shown that bubbles increase with liquidity in the market. The ability to purchase assets on margin, higher cash to asset ratios for a given endowment, and an absolute increase in cash all lead to greater bubbles. (King et al., 1993; Caginalp et al.; Haruvy and Noussair, 2006) In the treatment group, we expect the poor to borrow more than the rich to facilitate asset purchases, which should ease the liquidity constraints on momentum. Relative to the first stage, we expect higher asset price paths in both the equal and unequal sessions due to the ability of traders to buy on margin.

The third stage retains leverage and adds the Joneses effect. After the 1st and 3rd periods of the 15-period session, the trader(s) with the greatest number of asset shares stands and is recognized with applause by the other traders. Traders learn early in the session that there is a status for holding a high number of shares, even though accumulating more shares may not be financially rewarding if the price is above fundamental value. We expect that the status incentive encourages traders, especially the poor traders, to borrow to purchase assets, which increases price momentum and inflates the bubble. Schoenberg and Haruvy (2012) are the first to introduce social effects in a manner similar to ours. After each period, all traders observe either the highest account total (cash plus the market value of shares) of the leader, or the lowest account total of the laggard. They find that average asset prices are higher in sessions where traders are informed of the highest account total, and lower when traders are informed of the lowest account total. Further, they survey trader satisfaction and find that satisfaction ratings increase for the trader that is the leader, decrease for the trader that is the laggard, and are lower for non-leaders when given the highest account total than for non-laggards when given the lowest account total. These results are consistent with the notion that relative status is an important part of traders' utility functions.

Our Stage 1 results show that the unequally endowed sessions are more likely to experience both underpricing and overpricing relative to the equally endowed sessions. This result is consistent with a momentum effect that is either dampened from liquidity constraints by poor traders or enhanced from the concentrated liquidity among the rich traders. When leverage is added in Stage 2, we find consistent underpricing in the unequal sessions and lower average prices, again consistent with dampened momentum effects. Poor traders do not take advantage of the ability to borrow interest-free from the experimenter. The results from Stage 3 with the Joneses effect added are strikingly different. They show that the unequal sessions experience higher amplitude, relative deviation, and average prices than the equal sessions. In addition, poor traders are much more active in the early periods than they are in the other stages.

In sum, we observe that unequal initial endowments and the presence of a Joneses effect lead to substantial overpricing as compared to situations where one or both factors is absent. The bubble is driven in part by stronger demand for the asset and more aggressive borrowing by the low-wealth traders. To the extent that these results transfer to real economies, they show that wealth inequality and access to credit facilitate formation of a leveraged bubble, but the bubble may not emerge until psychological contagion is sufficiently strong so that holding the asset becomes an important status benchmark.

2. Experimental Design

This section describes our experimental design, including participant recruiting and the structure of each session. It describes the assets that participants traded, the three stages of the experiment, and the post-session assessment.

2.1 Recruiting and Session Structure

We generally follow and build upon the classic 15-period asset market experiment of SSW. We conducted a total of 37 sessions at the Behavioral Business Research Lab at the University of Arkansas from April 2016 to September 2017. Each session included 6 participants (traders) recruited from a pool of undergraduate students across all majors at the University of Arkansas, though the bulk of the participants were business and economics majors. Traders could not have participated in a similar asset market experiment, nor could they repeat participation in this experiment. Traders were randomly seated in cubicles in a computer laboratory, so they could not observe other traders' screens. They did, however, have an unobstructed view of the experimenter. They were not allowed to communicate with each other, nor were they allowed to use personal electronic devices.

Each session began with an introduction that included time to read the printed instructions. The experimenter then read aloud the first two pages of instructions, which contain the most important information. Traders could raise their hands with questions, and the experimenter answered questions individually. Two practice periods were run for participants to familiarize themselves with the trading interface. A quiz followed to test the participants' understanding, and the experimenter individually checked the answers of each trader, followed by a brief explanation of all the questions to the traders. The 15 trading periods then started. In each period, traders had 2 minutes and 15 seconds to buy or sell shares unless the trade violated leverage constraints or the no-shorting constraint. At the end of each session, traders completed personal assessment information.

Sessions lasted approximately 90 minutes, and traders were paid a $7 show-up fee with additional payments linked to cash held at the end of trading, a coin-flipping lottery based on risk preference responses, and the score from a cognitive test. Traders earned an average of $21.61 from the experiment.

2.2 Assets and Trading

Assets, which we call shares, are modeled as in SSW. Shares have a finite life of 15 periods and become worthless at the end of the session. The expected value of a share declines from 360 to 0 through the 15 periods. At the end of each period, one of four randomly drawn dividends, which are 0, 8, 28, or 60, is paid to the share's holder. The sequence of the 15 dividends is preset by the experimenter, fixed for all sessions, and unknown to traders.

2.3 Baseline Conditions

We run three stages of the experiment to observe the cumulative effects from (1) endowment inequality; (2) leverage; and (3) the "Joneses Effect." The baseline conditions described in this section apply to all stages.

In each stage, we run six[26] sessions where the benchmark group of traders receive equal initial endowments, and six sessions where traders receive initial unequal endowments. In the unequal endowment sessions, three randomly chosen traders are "rich," and three are "poor." The aggregate endowments are the same across the equal and unequal sessions; only the distribution differs. At the end of a session, traders receive payments in U.S. dollars at an exchange rate of 400 lab cash to $1 dollar.

Prior to the start of the session, we inform the traders as to whether the endowment distribution is equal or unequal. In the unequal sessions, traders are privately and individually informed whether their endowment type is "high" or "low," and that half of the subjects have high endowments, and the other half have low endowments. They are unaware, however, of the exact endowment of the opposite trader type.

2.4 Stage 1

In Stage 1, the benchmark sessions have equal endowments while the treatment sessions have unequal endowments. No borrowing is allowed and no Joneses effect is present. Traders are endowed in the equal sessions with 2160 laboratory (lab) cash and 6 shares. In the unequal sessions, three randomly chosen "rich" traders receive 3240 lab cash and 9 shares; the three "poor" traders are endowed with 1080 lab cash and 3 shares.

[26] We ran seven sessions with equal endowment in the first stage.

2.5 Stage 2

Stage 2 introduces leverage by allowing traders to borrow at a zero-interest rate up to 75% of the current market value of their shareholdings, which is determined by the most recent trading price. Each trader receives an additional $5 beyond the show-up fee as a cushion for bankruptcy. Traders with negative ending cash balances at the end of the session forfeit a portion of the cushion up to the maximum of $5. Again, there are two session types. In the equal endowment sessions, each trader is endowed with 360 lab cash and 6 shares. In the treatment sessions, three randomly chosen rich traders are endowed with 540 lab cash and 9 shares, and three poor traders are endowed with 180 cash and 3 shares. For Stages 2 and 3, we significantly reduce the initial cash endowment from Stage 1 to induce borrowing. Consequently, we are unable to compare bubbl3e outcome levels between Stage 1 and the other two stages, but stages 2 and 3 are directly comparable.

2.6 Stage 3

Stage 3 introduces the Joneses Effect. At the end of period 1, with no previous notice, the experimenter enters the room and says "I would like to recognize the person or persons holding the highest number of shares in the market. Look at your computer screen. If you hold the number of shares that is equal to the highest number of shares held in your market, please stand up. Let's all give them a round of applause." After applause, experimenter says: "You can sit now. We will recognize the people with the highest number of shares one more time after period 3." The experimenter repeats the statement at the end of period 3; no recognitions are performed thereafter. Although traders can see the person that stands up for recognition, they cannot identity that trader in the computer simulation. Additionally, from period 2 until the end of the session, a real-time display constantly appears on each trader's screen with the number of shares held by the person with the most shares in the market.

2.4 Market Setting

As in SSW, traders trade in a continuous double-auction market. The open orders and transacted orders are visible to the traders in the real time, along with a graphical representation of transaction prices. Each trader’s cash balance and number of shares, as well as the most recent trading price are constantly displayed on his/her individual screen. In stages 2 and 3, the trader’s current maximum borrowing limit is also displayed. At the end of each period, the screen shows the current dividend drawn and the updated balance information to the traders. There are 15 periods in each session, and traders have 2 minutes and 15 seconds to trade per session. Dividends are added to cash balances, which, along with shares, carry over to subsequent periods.

2.5 Trader Characteristics

Immediately after a session is concluded, traders complete a computerized questionnaire, which collects demographic information and assesses risk preference and cognitive ability. Demographic questions collect information about the traders’ gender, age, year in college, and major.

Each trader is asked to choose one of six lotteries, similar to the lotteries used by Eckel and Grossman (2002), to elicit risk preference. The experimenter conducts the chosen lottery, privately and individually, just before the trader receives cash payment, which includes any payment from the lottery outcome. Given that the lottery question does not distinguish degrees of risk-seeking behavior (Charness *et al.* (2013), a second question asks “In general, do you try to avoid taking risks or are you a person who is comfortable taking risks?”

Traders’ cognitive abilities are assessed with a three-question Cognitive Reflection Test (CRT). (Frederick (2005) The three questions are:

(1) A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost?

(2) If it takes 5 machines 5 min to make 5 widgets, how long would it take 100 machines to make 100 widgets?

(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

For each question answered correctly, the trader receives an additional $0.25 payment.

Table 1 reports summary statistics of trader characteristics. We recruited 222 traders, of which 126 were male and 96 were female. The mean age was 21.8, and 51.8% were economics or business majors. In general, trader characteristics do not vary significantly across different sessions and experimental stages.

Table 1. Summary Statistics of Trader Characteristics

Summary statistics of the trader characteristics by stage. Stage 1 includes multiple sessions with equal and unequal treatments; Stage 2 allows traders to buy shares on margin; Stage 3 introduces the Joneses effect. *Age* is the age of the trader at the time of experiment. *Gender* is a dummy variable that equals 1 if a trader is male, and 0 otherwise. *No. correct in CRT* is the number of questions the trader answers correctly in the three-question Cognitive Reflection Test based on Frederick (2005). *Patience* is the response of the traders to the following question: "Are you generally an impatient person, or someone who always shows great patience?", where the most impatient equals 0 and the most patient equals 1. *Econ/Business major* is a dummy variable that equals 1 if the trader is an economics or business major, and 0 otherwise.

	Stage 1						Stage 2						Stage 3					
	Equal			Unequal			Equal			Unequal			Equal			Unequal		
	N	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.
Age	35	23.86	5.87	41	22.88	2.62	36	20.64	1.50	36	20.31	2.42	36	21.81	4.13	36	21.50	1.73
Gender (Female=0)	36	0.50	0.51	42	0.64	0.48	36	0.61	0.49	36	0.53	0.51	36	0.39	0.49	36	0.72	0.45
No. correct in CRT	36	1.53	1.16	42	1.31	1.00	36	1.44	0.97	36	1.08	1.08	36	1.28	1.23	36	1.25	1.13
Patience (Impatient=0)	36	6.81	1.69	42	5.67	2.25	36	7.08	2.17	36	6.81	1.95	36	5.64	2.37	36	6.36	2.22
Econ/Business major	36	0.44	0.50	42	0.69	0.47	36	0.69	0.47	36	0.67	0.48	36	0.36	0.49	36	0.58	0.50

To measure risk preference, traders chose one of six lotteries, and we ranked the lotteries so that Lottery 1 was the safest and Lottery 6 was the riskiest. The mean choice was 3.42, reflecting moderate risk-seeking. The mean response to the second question asking the trader to choose on a scale from 0 (risk avoidance) to 10 (risk seeking) her willingness to take risks in general was 5.71, indicating that traders had a slightly greater risk taking preference than that suggested by the lottery response.

The mean CRT score of 1.31 is similar to what previous studies have found. Frederick (2005) found a meant score of 1.24 after administering the CRT in 11 locations including universities, social events, and online.

3. Bubble Metrics, Hypotheses and Results

In this section, we explain the three metrics used to compare bubble dynamics. We also state our three hypotheses and present the results.

3.1 Bubble Metrics

We assess bubbles using three common metrics. Amplitude is a widely used metric that measures the overall degree of price change, scaled by the fundamental value of the asset, throughout the life of the asset. (Haruvy and Noussair (2006); Huber and Kirchler (2012); Cheung *et al.* (2014); Andrade *et al.* (2015). It is measured as follows:

$$Amplitude = max\{(\overline{P_t} - f_t)/f_t\} - min\{(\overline{P_t} - f_t)/f_t\}$$

where $\overline{P_t}$ is the mean asset price and f_t is the fundamental value, both at period *t*. Stöckl *et al.* (2010) develop and propose two alternative bubble measures, relative absolute deviation (RAD) and relative deviation (RD), that better capture mispricing and overvaluation, and are less sensitive to the choice of parameters in the measurement. These metrics are also widely used in the literature. (Stöckl *et al.* (2015); Noussair and Tucker (2016) RAD and RD are quantified as follows:

$$RAD = \frac{1}{15}\sum_{t=1}^{15} |\overline{P_t} - FV_t|/|\overline{FV}|$$

$$RD = \frac{1}{15}\sum_{t=1}^{15} (\overline{P_t} - FV_t)/|\overline{FV}|$$

where $\overline{P_t}$ is the mean asset price at period *t*, FV_t is the fundamental value at period t, and $\overline{FV}$ is the mean fundamental of the market, which is 192 in our study.

3.2 Endowment Inequality

H1: Asset bubbles are larger when traders have unequal initial endowments rather than equal initial endowments, holding total endowment fixed.

We hypothesize that asset bubbles will be larger in the unequal sessions relative to the equal sessions because the concentrated liquidity among rich traders will boost price momentum, and these effects will outweigh liquidity constraints among the poor traders that weaken momentum. In the absence of leverage or a Joneses effect, we have no theoretical reason to believe that the concentrated liquidity effect will dominate the liquidity constraint effect. Indeed, we just as easily could have presented the opposite hypothesis. Ultimately, the outcome is empirically determined, and it may depend on the randomly assigned trader characteristics of the rich and poor traders.

We test H1 in Stage 1 of the experiment, where traders have equal initial endowments in the benchmark sessions and unequal initial endowments in the treatment sessions. Figure 1 shows the volume-weighted mean price and the mean trading volume by period of the benchmark and treatment sessions. The left panel shows that neither the equal nor unequal sessions produced significant bubbles relative to fundamental value. However, mean prices from the unequal sessions are much lower than the fundamental value during the first eight periods, suggesting that liquidity constraints may have dampened the price path. Consistent with this view, the right panel shows that mean trading volumes in the unequal sessions start out far lower and are less volatile across all periods than mean trading volumes in the equal sessions.

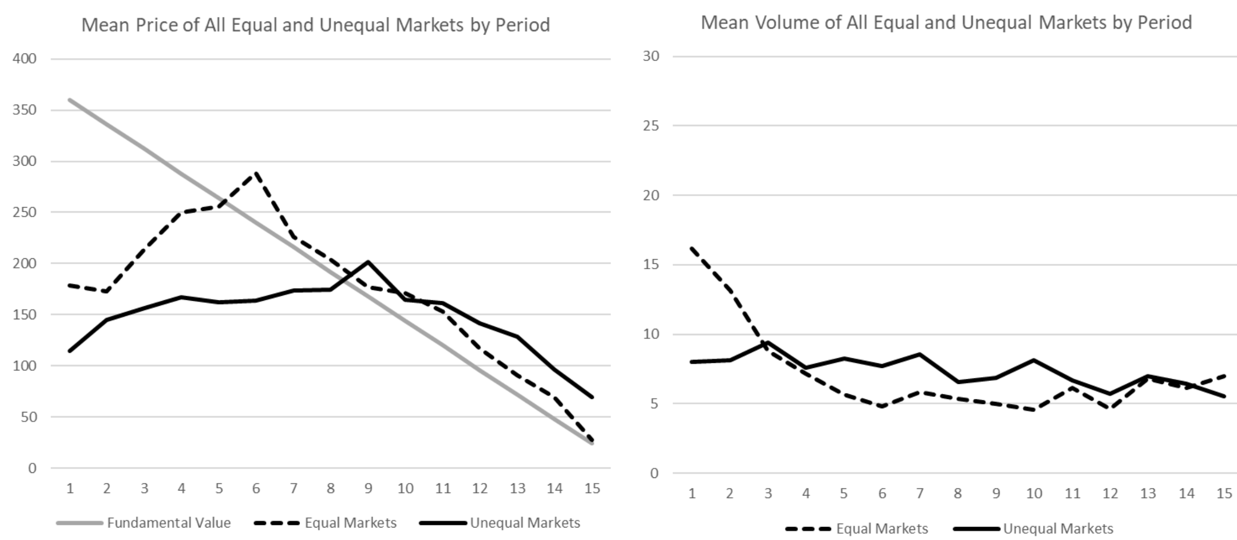


Figure 1. Trading Prices and Volume of Stage 1

Mean trading prices and the mean volume of equal and unequal markets by period for Stage 1, which includes multiple sessions with equal and unequal treatments. The left panel shows plots of mean prices, and the right panel shows plots of mean volume.

Panel A of Table 2 report Stage 1 summary statistics of the three bubble metrics by session. Mean amplitude is slightly lower in the unequal sessions, relative absolute deviation is higher, and relative deviation is lower, reflecting the stronger underpricing in those sessions. Panel B of Table 2 reports Mann-Whitney-Wilcoxon Rank-Sum tests at the session level. We find no statistically significant difference between the two treatments in terms of amplitude and RD, but the higher RAD is statistically different at the 5% level. This result is consistent with the price path observed in Figure 1. If anything, unequal initial endowments produce bubbles where prices are below fundamental value, consistent with weak momentum driven by liquidity constraints.

Table 2. Bubble Measures Comparison from Inequality

Comparison of bubble measures from stage 1. Stage 1 includes multiple sessions with equal and unequal treatments. Panel A reports mean bubble measures by session. $Amplitude = \max\left\{\frac{\overline{P_t} - f_t}{f_t}\right\} \min\left\{\frac{\overline{P_t} - f_t}{f_t}\right\}$, $RAD = \frac{1}{15}\sum_{t=1}^{15}\frac{|\overline{P_t} - FV_t|}{|\overline{FV}|}$, and $RD = \frac{1}{15}\sum_{t=1}^{15}(\overline{P_t} - FV_t)/|\overline{FV}|$. Panel B reports Wilcoxon Rank-sum Test results of bubble measures between equal and unequal endowment sessions.

Panel A: Bubble Measures

Equal Endowments				Unequal Endowments			
Session	Amplitude	RAD	RD	Session	Amplitude	RAD	RD
1	0.894	0.166	-0.079	1	1.422	0.495	0.069
2	1.375	0.297	0.102	2	0.408	0.201	-0.186
3	1.739	0.317	-0.102	3	0.989	0.358	-0.178
4	1.075	0.269	-0.136	4	1.189	0.522	-0.394
5	1.111	0.245	-0.188	5	1.281	0.461	-0.304
6	1.067	0.234	-0.128	6	1.306	0.645	0.34
				7	1.086	0.497	-0.388
Mean	1.186	0.248	-0.091	Mean	1.121	0.463	-0.16

Panel B: Wilcoxon Rank-sum Test between Equal and Unequal Treatments

	Amplitude	RAD	RD
z-stat	0.000	2.286	-1.143
P-value	1.000	0.022	0.253

We also evaluate how prices deviate from the fundamental value in the two treatments. Following Haruvy and Noussair (2006), we test whether the mean price per period is statistically different from the fundamental value, and if so, in which direction. Specifically, we test if $D_{period} = Period\ mean\ price - Fundamental\ value$ is statistically different from 0. We find that the mean of D_{period} for the equal endowment treatment is -16.95 (S.D. = 7.92, *p*-value = 0.035) and that the mean of D_{period} for the unequal treatment is -28.47 (S.D. = 10.95, p-value = 0.011). These results indicate a significant negative deviation of price from fundamental value in both equal and unequal sessions. We test further, at the period level of observation, whether the price deviation from the fundamental value is different between equal and unequal sessions. The results show that the price deviation differences are not statistically significant (T = -1.01, *p*-value = 0.316).

In sum, in the absence of leverage and the Joneses effect, the unequal distribution of endowments among traders seems to weaken momentum effects, which makes asset bubbles where prices are significantly above fundamental value less likely to form. This observation is analogous to a housing market where demand is weak because relatively low-wealth households do not have the savings to purchase homes and they have limited access to credit. Cynamon and Fazzari (2016) argue that the high inequality in the U.S. economy combined with tighter borrowing constraints on the bottom 95% of households help explain the slow recovery from the Great Recession.

3.3 Inequality and Leverage

H2: Asset bubbles are larger when traders have unequal initial endowments rather than equal initial endowments, holding total endowment fixed, and when all traders can leverage share values by borrowing at a zero-interest rate from the experimenter.

We test H2 in Stage 2 of our experiment. As in Stage 1, traders either have equal or unequal endowments in two different treatments, while the total endowment in the market are constant. Traders can borrow up to 75% of the current market value of their shareholdings, which is determined by the most recent trading price. We significantly reduced the initial cash endowment from that in Session 1 to induce borrowing especially among poor traders. Although all traders have access to liquidity given the ability to buy on margin, we should observe poor traders taking on the most leverage, which relaxes liquidity constraints and increases the momentum effect (Day & Chen 1993). We hypothesize that the momentum effect will be greater in the unequal sessions than the equal sessions because the concentration of wealth among the rich combined with leverage by the poor should induce more buying activity in the early rounds

The results do not support H2. The two charts in Figure 2 shows the volume-weighted mean price and the mean trading volume, respectively, by period for the two session types. From the left panel, we observe that mean prices from both the equal and unequal sessions show large negative bubbles relative to fundamental value before period 8. Modest bubbles emerge in both session types in later periods. The right panel of Figure 2 shows that trading volume in early periods is higher in the unequal sessions as expected, but trading in the unequal sessions declines more sharply than trading in the equal sessions throughout the 15 periods.

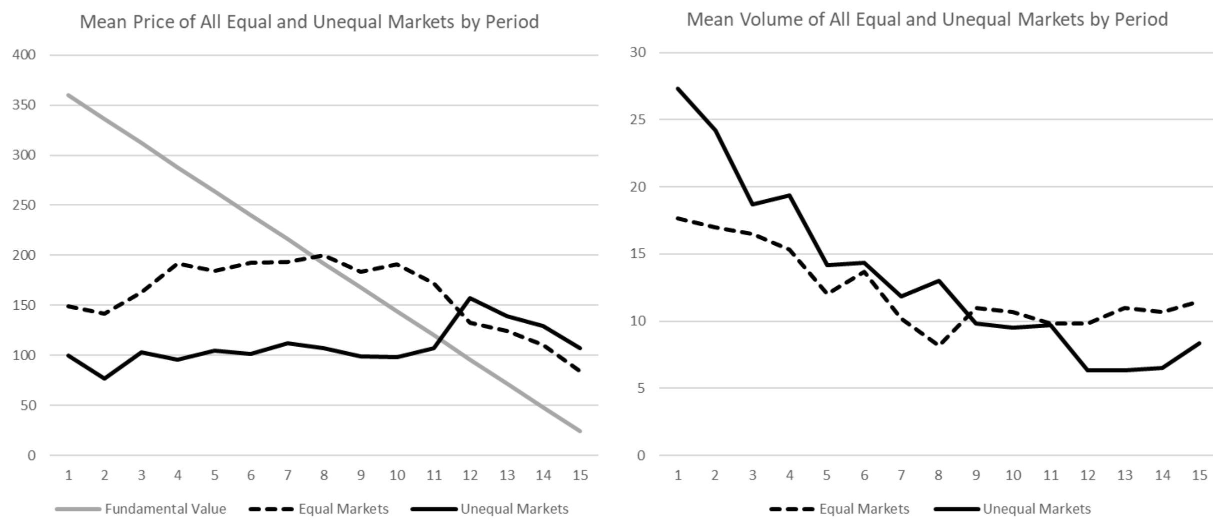


Figure 2. Trading Prices and Volume of Stage 2

Mean trading prices and the mean volume of equal and unequal markets by period for Stage 1, which includes multiple sessions with equal and unequal treatments. The left panel shows plots of mean prices, and the right panel shows plots of mean volume.

Bubble metrics show no statistical difference between the equal and unequal sessions in Stage 2. Panel A of Table 3 reports the three bubble metrics by session. As with Stage 1 results, unequal session means show lower amplitude, higher RAD, and lower RD relative to equal-session means. Mann-Whitney-Wilcoxon Rank-Sum tests at the session level, reported in the panel B of Table 3, show no statistically significant differences between the two session types for all three bubble measurements.

Table 3. Bubble Measures Comparison from Inequality and Leverage

Comparison of bubble measures from stage 2. Stage 2 allows traders to buy shares on margin. Panel A reports mean bubble measures by session. $Amplitude = \max\left\{\frac{\overline{P_t}-f_t}{f_t}\right\} \min\left\{\frac{\overline{P_t}-f_t}{f_t}\right\}$, $RAD = \frac{1}{15}\sum_{t=1}^{15}\frac{|\overline{P_t}-FV_t|}{|\overline{FV}|}$, and $RD = \frac{1}{15}\sum_{t=1}^{15}(\overline{P_t}-FV_t)/|\overline{FV}|$. Panel B reports Wilcoxon Rank-sum Test results of bubble measures between equal and unequal endowment sessions.

Panel A: Bubble Measures							
	Equal Endowments				Unequal Endowments		
Session	Amplitude	RAD	RD	Session	Amplitude	RAD	RD
1	2.060	0.549	0.303	1	2.272	0.288	0.061
2	2.429	0.206	-0.188	2	0.945	0.553	-0.226
3	0.082	0.584	-0.463	3	0.422	0.608	-0.400
4	0.865	0.420	0.047	4	0.421	0.679	-0.562
5	0.996	0.553	-0.388	5	0.729	0.824	-0.643
6	1.829	0.468	0.196	6	1.085	0.532	-0.124
Mean	1.039	0.498	-0.160	Mean	0.756	0.654	-0.420

Panel B: Wilcoxon Rank-sum Test between Equal and Unequal Treatments			
	Amplitude	RAD	RD
z-stat	-0.160	1.441	-1.281
P-value	0.873	0.150	0.200

Based on the period-level observations, prices do not significantly deviate from fundamental value in the equal endowment sessions (T = -1.313, p-value = 0.193), but they do deviate from fundamental value in the unequal sessions (T = -4.630, p-value = 0.000). The cross-treatment T-test indicates that the prices are statistically significant between the two session types, where both types exhibit negative bubbles, but unequal sessions have significantly lower prices than the equal sessions (T = -4.003, p-value = 0.000).

We conclude, unexpectedly, that asset markets that combine unequal initial endowments with leverage do not produce larger bubbles than asset markets that combine equal initial endowments with leverage.

3.3 Inequality, Leverage and the Joneses Effect

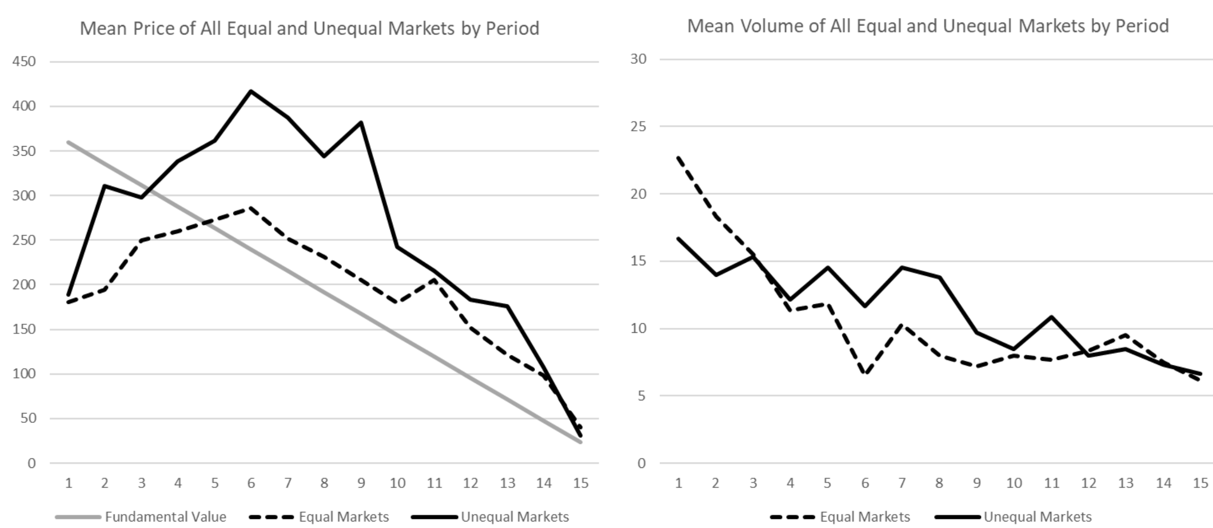
H3: Asset bubbles are larger when: (i) traders have unequal initial endowments rather than equal initial endowments, holding total endowment fixed; (ii) traders can leverage share by borrowing at a zero-interest rate from the experimenter; and (iii) traders are incentivized to purchase shares in the early rounds by a "Keeping up with the Joneses" effect.

Stage 3 of the experiment tests H3. The only difference between Stage 2 and Stage 3 is that the experimenter enters the trading room after periods 1 and 3 and recognizes the person(s) with the highest shares, who then receives a round of applause by other traders. Relative to equal sessions, we expect unequal sessions to produce bigger bubbles because poor traders who begin with 3 shares will observe wide gaps between their own asset holdings and the top asset holder who is surely a rich trader that began with 9 shares. The gaps between traders will be smaller in the equal sessions because each trader begins with 6 shares, so the Joneses effect will be smaller.

In support of H3, we do observe significant bubbles in Stage 3, especially in the unequal sessions, which contrasts sharply with Stage 2 results. The mean price trend and trading volume of the two session types are exhibited in Figure 3. The bubble pattern is obvious. The left panel shows that the unequal sessions produce a higher mean price in 14 of 15 periods. The right panel shows that the unequal sessions produce a higher trading volume in 9 of 15 periods, especially during the middle part of the session when the bubble grows most dramatically.

Figure 3. Trading Prices and Volume of Stage 3

Mean trading prices and the mean volume of equal and unequal markets by period for Stage 3, which adds the Joneses effect. The left panel shows plots of mean prices, and the right panel shows plots of mean volume.



We report the bubble metrics and comparison tests for Stage 3 in Table 4. Summary statistics in Panel A shows that all three metrics are higher for the unequal session than the equal sessions, and both session types have positive bubbles as shown by the positive value of RD. Panel B reports the Mann-Whitney-

Wilcoxon Rank-Sum tests at the session level. The difference in amplitude between the unequal and equal sessions is statistically significant at the 5% level, and the difference in RD is statistically significant at the 10% level.

Table 4. Bubble Measures Comparison from Inequality, Leverage and the Joneses Effect

Comparison of bubble measures from stage 3. Stage 3 adds the Joneses effect. Panel A reports mean bubble measures by session. $Amplitude = \max\left\{\frac{\overline{P_t}-f_t}{f_t}\right\} \min\left\{\frac{\overline{P_t}-f_t}{f_t}\right\}$, $RAD = \frac{1}{15}\sum_{t=1}^{15}\frac{|\overline{P_t}-FV_t|}{|\overline{FV}|}$, and $RD = \frac{1}{15}\sum_{t=1}^{15}(\overline{P}_t - FV_t)/|\overline{FV}|$. Panel B reports Wilcoxon Rank-sum Test results of bubble measures between equal and unequal endowment sessions.

Panel A: Bubble Measures

Equal Endowments				Unequal Endowments			
Session	Amplitude	RAD	RD	Session	Amplitude	RAD	RD
1	1.509	0.287	-0.239	1	2.370	0.071	0.022
2	1.853	0.387	0.207	2	5.460	1.332	1.159
3	2.276	0.609	0.005	3	1.939	0.376	0.221
4	2.230	0.442	-0.353	4	2.714	0.502	0.147
5	1.665	0.993	0.932	5	3.027	0.740	0.390
6	3.693	0.076	0.028	6	8.281	1.383	1.232
Mean	2.269	0.409	0.021	Mean	3.240	0.559	0.376

Panel B: Wilcoxon Rank-sum Test between Equal and Unequal Treatments

	Amplitude	RAD	RD
z-stat	2.082	0.801	1.761
P-value	0.037	0.423	0.078

The period-level T-test for the equal and unequal sessions shows statistically significant price deviation from fundamental value (T = 4.885, p-value = 0.000). In contrast, the equal treatment does not exhibit statistically significant price deviation from fundamental value (T = 1.379, p-value = 0.171). The cross-treatment T-test indicates that differences in prices are statistically significant between the two treatments, and the unequal sessions have significantly higher mean prices than the equal sessions (T = 3.2100, p-value = 0.002).

In sum, Stage 3 results show that unequal endowments combined with leveraging and the Joneses effect create significantly greater bubbles than when equal endowments combine with leveraging and the Joneses Effect.

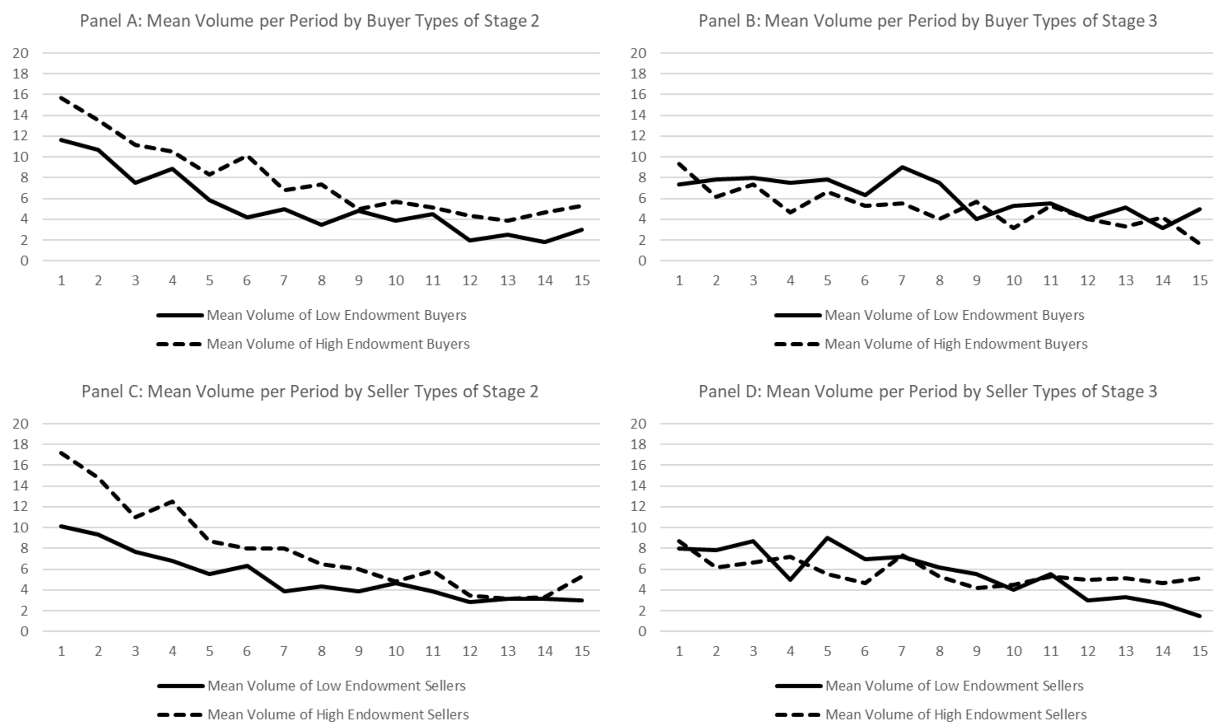
3.4 Bubble Formation Analysis

Taken together, results from the three stages of our experiment suggest that social status plays a strong role in facilitating asset bubbles. Adding the Keeping up with the Joneses incentive in Stage 3 produced statistically significant positive bubbles relative to the negative bubbles observed in Stages 1 and 2 .

We can better understand how social status affects bubble formation by directly comparing stages 2 and 3. If the Joneses effect is strong, we would expect poor traders to buy more assets relative to rich traders in early periods compared with markets with no Joneses effect. Panels A and B of Figure 4 plot mean buy volumes by period separately for rich and poor traders for stages 2 and 3, respectively. Panel A shows that when the Joneses effect is absent, rich traders consistently buy more shares than poor traders. In Panel B, however, poor traders on average buy more shares than rich traders in 10 of 15 periods. Similar effects exist from the sellers' side. Panel C shows that in the absence of the Joneses effect, rich traders consistently sell more shares than poor traders. Panel D shows that when the Joneses effect is introduced, poor traders more actively sell shares in 6 of 15 periods. We conclude that bubbles are partly driven by higher asset demand by poor traders.

Figure 4. Trading Volume in Stages 2 and 3

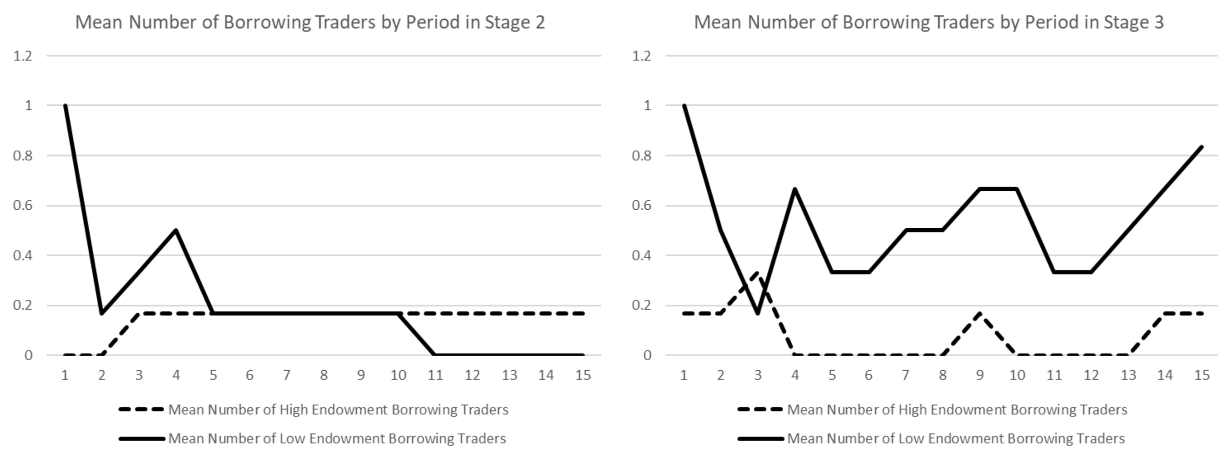
Figure 4 plots the mean trading volume by period in Stages 2 and 3. Panels A and B plots the mean trading volume by buyer types in Stages 2 and 3, respectively. Panels C and D plots the mean trading volume by seller types in Stages 2 and 3, respectively.



We further compare the borrowing patterns of the high and low endowed traders in Stages 2 and 3. If the Joneses Effect is strong, we would expect poor traders to borrow more frequently than the rich traders in the environment where the Joneses Effect is present. Figure 5 plots the mean number of traders that have a net borrowing at the end of each periods by trader endowment types. The left panel shows the plots for Stage 2 and the right one shows those for Stage 3. It is obvious that in stage 3, the number of borrowing traders are similar most of the time between rich and poor. However in Stage 3, there are consistently more poor borrowers than rich borrowers starting from period 4, the period following the two recognitions of the trader with the highest number of shares. Note that, when the trader is still in net borrowing position by the end of the 15 periods, he is considered as having a bankruptcy, as all shares become worthless at that moment. Figure 5 shows that there are more bankruptcy occurs for poor traders in Stage 3 than in Stage 2, indicating a more aggressive borrowing behavior for the poor traders in Stage 3 that results in more financial instability by the end of the trading. We therefore conclude that the bubbles are also partially driven by the excessive borrowing behavior of the poor traders when the Joneses Effect is present.

Figure 5. Number of Borrowers in Stages 2 and 3

Figure 5 plots the mean number of net borrowers in Stages 2 and 3. The left panel shows the mean number of net borrowers in Stage 2, and the right panel shows that in Stage 3.



4. Conclusion

Literature has shown that leveraged real estate bubbles have become more frequent, increasing financial instability and imposing extensive damage on economies. Also, low- and middle-income households are increasingly prone to over-indebtedness and default on credit cards, housing, and auto loans. Part of the reason is because wealth inequality in the U.S. and many other countries has increased over the last couple decades, and the poor households want to keep up with the living standards and social class with their relatively rich neighbors, which is so-called "keeping up with the Joneses." Hence, the poor households may end up with buying a house by taking on too much debt, which eventually causes greater asset bubbles and financial instability. In a lab setting, we test how wealth inequality, borrowing, and "keeping up with the Joneses" effect influence asset bubbles. We recruit undergraduate students to trade assets in a computer lab, and subsequently study the trading results. We find that wealth inequality alone does not result in different asset bubble dynamics relative to markets with equal initial endowments. Instead, it is the wealth inequality, combining with leveraging and "keeping up with the Joneses" effect that creates asset bubbles.

Additionally, we observe that the low endowment traders are more active in trading and are more aggressive in borrowing when the Joneses effect is present, and this partially contributes to the asset bubbles.

References

Allen, L., Jagtiani, J., Peristiani, S., Saunders, A., 2004. The role of bank advisors in mergers and acquisitions. Journal of Money, Credit and Banking, 197-224

Andrade, E.B., Odean, T., Lin, S., 2015. Bubbling with excitement: an experiment. Review of Finance 20, 447-466.

Bao, J., Edmans, A., 2011. Do investment banks matter for M&A returns? The Review of Financial Studies 24, 2286-2315

Billett, M.T., King, T.H.D., Mauer, D.C., 2004. Bondholder wealth effects in mergers and acquisitions: New evidence from the 1980s and 1990s. The Journal of Finance 59, 107-135

Billett, M. T., & Qian, Y., 2008. Are overconfident CEOs born or made? evidence of self-attribution bias from frequent acquirers. Management Science, 54(6), 1037-1051.

Bonacich, P., 1972. Factoring and weighting approaches to status scores and clique identification. Journal of Mathematical Sociology, 2(1), 113-120.

Boot, A. W., Greenbaum, S. I., & Thakor, A. V., 1993. Reputation and discretion in financial contracting. The American Economic Review, 1165-1183.

Bowers, H.M., Miller, R.E., 1990. Choice of investment banker and shareholders' wealth of firms involved in acquisitions. Financial Management, 34-44

Burt, R. S., 1997. The contingent value of social capital. Administrative Science Quarterly, , 339-365.

Burt, R. S., 2005. Brokerage and closure: An introduction to social capital OUP Oxford.

Burt, R. S., 2010. Neighbor networks: Competitive advantage local and personal Oxford University Press.

Caginalp, G., Porter, D.P. and Smith, V.L., 2000a Momentum and overreaction in experimental asset markets. International Journal of Industrial Organization 18: 187–204.

Caginalp, G., Porter, D.P. and Smith, V.L., 2000b. Overreactions, momentum, liquidity, and price bubbles in laboratory and field asset markets. Journal of Psychology and Financial Markets 1(1): 24–48.

Cai, J., Walkling, R. A., & Yang, K., 2014. The price of street friends: Social networks, informed trading, and shareholder costs. Journal of Financial and Quantitative Analysis (JFQA), Forthcoming,

Cai, Y., & Sevilir, M., 2012. Board connections and M&A transactions. Journal of Financial Economics, 103(2), 327-349.

Charness, G., Gneezy, U., Imas, A., 2013. Experimental methods: Eliciting risk preferences. Journal of Economic Behavior & Organization 87, 43-51

Chava, S., Livdan, D., & Purnanandam, A., 2009. Do shareholder rights affect the cost of bank loans? Review of Financial Studies, 22(8), 2973-3004.

Clarke, J., Dunbar, C., & Kahle, K. M., 2001. Long-run performance and insider trading in completed and canceled seasoned equity offerings. Journal of Financial and Quantitative Analysis, 36(04), 415-430.

Cohen, L., Frazzini, A., & Malloy, C., 2008. The Small World of Investing: Board Connections and Mutual Fund Returns,

Cohen, L., Frazzini, A., & Malloy, C., 2010. Sell-side school ties. The Journal of Finance, 65(4), 1409-1437.

Cook, D. O., Kieschnick, R., & Van Ness, R. A., 2006. On the marketing of IPOs. Journal of Financial Economics, 82(1), 35-61.

Cooney, J. W., Madureirav, L., Singh, A. K., & Yang, K., 2015. Social ties and IPO outcomes. Journal of Corporate Finance,

Cooney, J., Madureira, L., Singh, A. K., & Yang, K., 2014. IPO underwriting syndicates: Do social ties help get a seat at the table? Available at SSRN 2179491,

Corwin, S. A., & Schultz, P., 2005. The role of IPO underwriting syndicates: Pricing, information production, and underwriter competition. The Journal of Finance, 60(1), 443-486.

Cronqvist, H., Makhija, A. K., & Yonker, S. E., 2012. Behavioral consistency in corporate finance: CEO personal and corporate leverage. Journal of Financial Economics, 103(1), 20-40.

Cheung, S.L., Hedegaard, M., Palan, S., 2014. To see is to believe: Common expectations in experimental asset markets. European Economic Review 66, 84-96

Chuluun, T., 2015. The role of underwriter peer networks in IPOs. Journal of Banking & Finance, 51, 62-78.

Chuluun, T., Prevost, A., & Puthenpurackal, J., 2014. Board ties and the cost of corporate debt. Financial Management, 43(3), 533-568.

Cynamon, B., Fazzari, S., 2016. Inequality, the Great Recession and slow recovery. Cambridge Journal of Economics 40, 373–399.

Day, R.H., Chen, P., 1993. Nonlinear dynamics and evolutionary economics. Oxford University Press Oxford.

Demarzo P. Kaniel R., Kremer I., 2008. Relative Wealth Concerns and Financial Bubbles. The Review of Financial Studies 21, 19-50.

Dunbar, C. G., 2000. Factors affecting investment bank initial public offering market share. Journal of Financial Economics, 55(1), 3-41.

Eckel, C.C., Grossman, P.J., 2002. Sex differences and statistical stereotyping in attitudes toward financial risk. Evolution and Human Behavior 23, 281-295.

El-Khatib, R., Fogel, K., & Jandik, T., 2015) CEO network centrality and merger performance. Journal of Financial Economics, 116(2), 349-382.

Engelberg, J., Gao, P., & Parsons, C. A., 2012. Friends with money. Journal of Financial Economics, 103(1), 169-188.

Faleye, O., Kovacs, T., & Venkateswaran, A., 2014. Do better-connected CEOs innovate more? Journal of Financial and Quantitative Analysis 49, 1201-1225.

Fogel, K., Jandik, T., & McCumber, W. R., 2015. CFO network centrality and private debt. Available at SSRN 2396268,

Fracassi, C., 2016. Corporate Finance Policies and Social Networks. Management Science 0, null

Fracassi, C., 2014. Corporate finance policies and social networks. AFA 2011 Denver Meetings Paper

Fracassi, C., & Tate, G., 2012. External networking and internal firm governance. The Journal of Finance, 67(1), 153-194.

Francis, B.B., Hasan, I., Sun, X., 2014. Does relationship matter? The choice of financial advisors. Journal of Economics and Business 73, 22-47

Fuller, K., Netter, J., Stegemoller, M., 2002. What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions. The Journal of Finance 57, 1763-1793

Frank, R.H., Levine, A.S. and Dijk, O., 2010. Expenditure Cascades. Available at http://ssrn.com/abstract=1690612 (last accessed May 2012).

Frederick, S., 2005. Cognitive reflection and decision making. Journal of Economic perspectives 19, 25-42.

Freeman, L. C., 1977) A set of measures of centrality based on betweenness. Sociometry, , 35-41.

Golubov, A., Petmezas, D., Travlos, N.G., 2012. When it pays to pay your investment banker: New evidence on the role of financial advisors in M&As. The Journal of Finance 67, 271-311

Graham, J. R., Harvey, C. R., & Puri, M., 2013. Managerial attitudes and corporate actions. Journal of Financial Economics, 109(1), 103-121.

Graham, J. R., Harvey, C. R., & Rajgopal, S., 2005. The economic implications of corporate financial reporting. Journal of Accounting and Economics, 40(1), 3-73.

Grinstein, Y., Hribar, P., 2004. CEO compensation and incentives: Evidence from M&A bonuses. Journal of Financial Economics 73, 119-143

Haruvy, E., Noussair, C.N., 2006. The effect of short selling on bubbles and crashes in experimental spot asset markets. The Journal of Finance 61, 1119-1157.

Heckman, J., 1979. Sample selection bias as a specification error. Econometrica 47, 153-161

Huber, J., Kirchler, M., 2012. The impact of instructions and procedure on reducing confusion and bubbles in experimental asset markets. Experimental Economics 15, 89-105.

Hunter, W.C., Jagtiani, J., 2003. An analysis of advisor choice, fees, and effort in mergers and acquisitions. Review of Financial Economics 12, 65-81

Hussam, R.N., Porter, D., Smith, V.L., 2008. Thar she blows: Can bubbles be rekindled with experienced traders? American Economic Review 98, 924-37.

Ishii, J., & Xuan, Y., 2014. Acquirer-target social ties and merger outcomes. Journal of Financial Economics, 112(3), 344-363.

Jackson, M. O., 2008. Social and economic networks Princeton University Press Princeton.

Jandik, D., Jandik, T., Xu, W., 2016. CEO Network Centrality and IPO Performance.

Jensen, M.C., 1986. Agency costs of free cash flow, corporate finance, and takeovers. The American economic review 76, 323-329

Jensen, M.C., Ruback, R.S., 1983. The market for corporate control: The scientific evidence. Journal of Financial economics 11, 5-50

Jenter, Dirk, and Fadi Kanaan. "CEO turnover and relative performance evaluation." The Journal of Finance 70.5 (2015): 2155-2184.

Kale, J.R., Kini, O., Ryan, H.E., 2003. Financial advisors and shareholder wealth gains in corporate takeovers. Journal of Financial and Quantitative Analysis 38, 475-501

Kaplan, S. N., Klebanov, M. M., & Sorensen, M., 2012. Which CEO characteristics and abilities matter? The Journal of Finance, 67(3), 973-1007.

Krigman, L., Shaw, W. H., & Womack, K. L., 2001. Why do firms switch underwriters? Journal of Financial Economics, 60(2), 245-284.

Labianca, G., & Brass, D. J., 2006. Exploring the social ledger: Negative relationships and negative asymmetry in social networks in organizations. Academy of Management Review, 31(3), 596-614.

Lang, L.H., Stulz, R., Walkling, R.A., 1989. Managerial performance, Tobin's Q, and the gains from successful tender offers. Journal of financial Economics 24, 137-154

Lang, L.H., Stulz, R., Walkling, R.A., 1991. A test of the free cash flow hypothesis: The case of bidder returns. Journal of Financial Economics 29, 315-335

Larcker, D. F., So, E. C., & Wang, C. C., 2013. Boardroom centrality and firm performance. Journal of Accounting and Economics, 55(2), 225-250.

Lins, K. V., et al., 2017. "Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis." The Journal of Finance 72(4): 1785-1824.

Li, K., Prabhala, N., 2007. Self-selection models in corporate finance. Handbook of corporate finance: Empirical corporate finance 1, 37

Liu, Y., 2010. The role of networks in the CEO and director labor market.

Loughran, T., & Ritter, J. R., 2002. Why don't issuers get upset about leaving money on the table in IPOs? Review of Financial Studies, 15(2), 413-444.

Malmendier, U., & Tate, G., 2005. CEO overconfidence and corporate investment. The journal of finance, 60(6), 2661-2700.

Malmendier, U., & Tate, G., 2008. Who makes acquisitions? CEO overconfidence and the market's reaction. Journal of Financial Economics, 89(1), 20-43.

Maloney, M.T., McCormick, R.E., Mitchell, M.L., 1993. Managerial decision making and capital structure. Journal of Business, 189-217

Mizruchi, M. S., & Potts, B. B., 1998. Centrality and power revisited: Actor success in group decision making. Social Networks, 20(4), 353-387.

Moeller, S.B., Schlingemann, F.P., Stulz, R.M., 2004. Firm size and the gains from acquisitions. Journal of financial economics 73, 201-228

Moeller, S.B., Schlingemann, F.P., Stulz, R.M., 2007. How do diversity of opinion and information asymmetry affect acquirer returns? The Review of Financial Studies 20, 2047-2078

Morck, R., Shleifer, A., Vishny, R.W., 1990. Do managerial objectives drive bad acquisitions? The Journal of Finance 45, 31-48

Kumhof, Michael, Romain Rancière, and Pablo Winant. 2015. "Inequality, Leverage, and Crises." American Economic Review, 105 (3): 1217-45.

Mian, A., Sufi, A., 2009. The consequences of mortgage credit expansion: Evidence rrom the U.S. mortgage default crisis. The Quarterly Journal of Economics, 1449-1496.

Nadauld, T., Sherlund, S., 2013. The impact of securitization on the expansionof subprime credit. Journal of Financial Economics 107, 454–476.

Nahapiet, J., & Ghoshal, S., 1998. Social capital, intellectual capital, and the organizational advantage. Academy of Management Review, 23(2), 242-266.

Newman, M., 2010. Networks: An introduction Oxford University Press.

Noussair, C.N., Tucker, S., 2016. Cash inflows and bubbles in asset markets with constant fundamental values. Economic Inquiry 54, 1596-1606.

Officer, M.S., Poulsen, A.B., Stegemoller, M., 2009. Target-firm information asymmetry and acquirer returns. Review of Finance 13, 467-493

Otto, C. A., 2014. CEO optimism and incentive compensation. Journal of Financial Economics, 114(2), 366-404.

Padgett, J. F., & Ansell, C. K., 1993. Robust action and the rise of the medici, 1400-1434. American Journal of Sociology, , 1259-1319.

Parrino, R., 1997. CEO turnover and outside succession A cross-sectional analysis, Journal of Financial

Economics 46, 165-197.

Proctor, C., & Loomis, C., 1951. Analysis of sociometric data. research methods in social relations: Part two, selected techniques.

Rajan, R., 2010. Fault Lines: How Hidden Fractures Still Threaten theWorld Economy. Princeton NJ: Princeton University Press.

Saez, E., Zucman, G., 2016. The Quarterly Journal of Economics (2016), 519–578.

Renneboog, L., Zhao, Y., 2014. Director networks and takeovers. Journal of Corporate Finance 28, 218-234

Rock, K., 1986. Why new issues are underpriced. Journal of Financial Economics, 15(1), 187-212.

Roll, R., 1986. The hubris hypothesis of corporate takeovers. Journal of business, 197-216.Sabidussi, G. (1966). The centrality index of a graph. Psychometrika, 31(4), 581-603.

Rosen, R.J., 2006. Merger momentum and investor sentiment: The stock market reaction to merger announcements. The Journal of Business 79, 987-1017

Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41-55

Rupasingha, A., Goetz, S.J., Freshwater, D., 2006. The production of social capital in US counties. The journal of socio-economics 35, 83-101

Schmidt, B., 2015. Costs and benefits of friendly boards during mergers and acquisitions. Journal of Financial Economics 117, 424-447

Servaes, H., 1991. Tobin's Q and the Gains from Takeovers. The Journal of Finance 46, 409-419

Servaes, H., Zenner, M., 1996. The role of investment banks in acquisitions. The Review of Financial Studies 9, 787-815

Seyhun, H. N., 1992. Why does aggregate insider trading predict future stock returns. The Quarterly Journal of Economics, 1303-1331.

Shiller, Robert J. 2005. Irrational Exuberance. 2nd ed. Princeton, NJ: Princeton University Press.

Smith, R.L., Kim, J.-H., 1994. The combined effects of free cash flow and financial slack on bidder and target stock returns. Journal of Business, 281-310

Smith, V.L., Suchanek, G.L., Williams, A.W., 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. Econometrica: Journal of the Econometric Society, 1119-1151.

Stöckl, T., Huber, J., Kirchler, M., 2010. Bubble measures in experimental asset markets. Experimental Economics 13, 284-298.

Stöckl, T., Huber, J., Kirchler, M., 2015. Multi-period experimental asset markets with distinct fundamental value regimes. Experimental Economics 18, 314-334.

Travlos, N.G., 1987. Corporate takeover bids, methods of payment, and bidding firms' stock returns. The Journal of Finance 42, 943-963

Wolff, E., 2016. Household Wealth Trends in the United States, 1962 to 2013: What Happened over the Great Recession? RSF: The Russell Sage Foundation Journal of the Social Sciences 2, 24-43.

Wikipedia, 2018. List of United States university campuses by enrollment. URL https://en.wikipedia.org/wiki/List_of_United_States_university_campuses_by_enrollment

Wooldridge, J. M., 2015. Introductory econometrics: A modern approach, Nelson Education.

Appendix

UNIVERSITY OF ARKANSAS

Office of Research Compliance
Institutional Review Board

April 4, 2017

MEMORANDUM

TO:	Weineng Xu Tim Yeager Cary Deck Li Hao
FROM:	Ro Windwalker IRB Coordinator
RE:	PROJECT CONTINUATION & MODIFICATION
IRB Protocol #:	16-04-672
Protocol Title:	*Asset Markets with Income Inequality*
Review Type:	☒ EXEMPT ☐ EXPEDITED ☐ FULL IRB
Previous Approval Period:	Start Date: 04/11/2016 Expiration Date: 04/10/2017
New Expiration Date:	04/10/2018

Your request to extend and modify the referenced protocol has been approved by the IRB. If at the end of this period you wish to continue the project, you must submit a request using the form *Continuing Review for IRB Approved Projects*, prior to the expiration date. Failure to obtain approval for a continuation on or prior to this new expiration date will result in termination of the protocol and you will be required to submit a new protocol to the IRB before continuing the project. Data collected past the protocol expiration date may need to be eliminated from the dataset should you wish to publish. Only data collected under a currently approved protocol can be certified by the IRB for any purpose.

This protocol has been approved for 400 total participants. If you wish to make *any* modifications in the approved protocol, including enrolling more than this number, you must seek approval *prior to* implementing those changes. All modifications should be requested in writing (email is acceptable) and must provide sufficient detail to assess the impact of the change.

If you have questions or need any assistance from the IRB, please contact me at 109 MLKG Building, 5-2208, or irb@uark.edu.

109 MLKG • 1 University of Arkansas • Fayetteville, AR 72701-1201 • (479) 575-2208 • Fax (479) 575-6527 • Email irb@uark.edu
The University of Arkansas is an equal opportunity/affirmative action institution.