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From the Editor

We are delighted to publish the June 2022 issue of *Review of Business*. This issue features four academic papers that span a diverse spectrum of business research topics, including post-pandemic business practice, the value of corporate networks in mergers and acquisitions (M&As), the impact of peer firms' initial public offerings on competitor's financing cost, and an inquiry into convertible bonds in China.

The lead article, "Rethinking Business Model for Drug Discovery, Post-COVID" by Mishra and Qi,[1] proposes a peer-to-peer business model for COVID-19 drug discovery. The model democratizes the drug discovery process and reduces drug prices by cutting the intermediaries that stand between biomedical researchers and future patients. With a signaling game-theoretic mechanism, this paper not only elucidates how the stakeholders strategically interact in this market using deception, adverse selection, and moral hazards, but also how to tame their interactions to improve overall performance. Using extensive simulations, the authors show that, in the non-fungible token (NFT) megafund, both senior and junior tranche investors get their principals fully repaid 99.9 percent of the time. With the help of innovation in financing, this paper shows that market micro-structure can help reduce health disparities in three ways. First, by participating in the drug discovery process, the underrepresented population can accelerate drug discovery for diseases unique to themselves. Historically, such diseases have been understudied due to a lack of funding and resources. Second, cutting out the middleman can significantly reduce drug-development costs, which will increase access to medicine. Finally, retail investors can also benefit from investing in drug discovery because the risk associated with the NFT is managed down to the level of debt.

In the second article, "The Economic Worth of the Firm's Interorganizational Relationships in Acquisitions: A Social Network Perspective," Jin, Liao, Wang, and Wang adopt the social network methodology in the M&A process to capture the target firms' network position and relate it to abnormal returns experienced by the acquiring firms on the announcements. With a sample of 728 completed acquisitions in the United States from 1990 to 2011, this paper documents positive stock market responses to the target's network centrality. The combined centrality and the relative centrality of the acquiring firm and the target firm enhance the performance of a particular acquisition. Also, the positive effects of the target firm's centrality on the acquirer's shareholder value creation are stronger when the acquisitions are related deals, or the acquirer has prior experience in the target's industry. This study offers a systematic analysis of whether and how a target firm's network position leads to the shareholder value creation of the acquirer and demonstrates that the externally derived network position and resources of the target firm can influence the stock market's valuation of M&A deals.

In the next article, "The Competitive Effects of IPOs on Industry Peers' Finance Contracting: Evidence from Bank Loans," Ren, Wu, and Francis raise

[1] This article was edited and processed by Dr. Hongfei (Frank) Tang. And it was originally for the COVID-19 special issue of January 2022. It is accepted in the regular issue of June 2022.

the question of how a successful IPO impacts the incumbent companies' bank loan terms, as the successful IPO will affect industry peers' bank loans via escalated product market competition and financing market competition. Using a difference-in-difference approach, the authors find that after the successful IPO, bank loans initiated for the industry's incumbent firms have significantly higher loan spread, higher likelihood of employing performance pricing provisions, and higher commitment fees; the syndicate loan structure for industry incumbents becomes more concentrated after successful IPOs in the industry; the number of lenders declines while lead bank share increases. With solid evidence and methodology, this paper reveals that the IPO competitive effects are more pronounced among firms in more intensive industrial competition and with higher levels of information asymmetry. It implies that IPO competitive effects impact the peers' bank loan terms via product market competition and financing market competition.

Liu, Shen, Wang, and Zhang contribute their work "Understanding Convertible Bond Issuances of Chinese Listed Firms" as the fourth article of this issue. This paper helps explain why Chinese firms issue convertible bonds. The paper is motivated by the observation that most convertible bonds issued by listed firms in China from 2003 to 2014 were converted to equity before the maturity date, a practice distinguish from their counterparts in the United States and the European Union, suggesting that the convertible bond in China is used as a backdoor equity financing instrument. Using a sample of 77 convertible debt, 655 straight debt, and 1089 seasoned equity issues in China from 2003 to 2014, the authors show that firms are more likely to issue convertible bonds rather than straight debt when the debt-related cost is low and stock price run-up is high. Compared to seasoned equity issuers, firms issue convertible bonds when the risk-free rate is low. The evidence suggests that while listed firms in China still seek equity financing first, they issue convertible bonds to take advantage of the interest rate deduction with the assurance to their investors that the convertibles can be converted to equities. In addition, most convertible bonds were underpriced on the offering date, suggesting convertible bond issuers do not exploit local investors in China.

We sincerely hope that both scholars and professionals will find this issue of *Review of Business* constructive and enlightening. We will continue to publish high-quality scholarly articles that answer the most imminent questions in the business fields.

Yun Zhu, Editor

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Rethinking Business Model for Drug Discovery, Post-COVID

Bud Mishra

Qianru Qi

Abstract

Motivation: The COVID pandemic underscores the need for fair access to health care. The unequal access to needed but patented, expensive medicines will exacerbate existing disparities among disadvantaged populations. For example, cancer gene therapy costs range from $373,000 for a single dose of CAR-T therapy Yescarta to $2.1 million for Zolgensma.

Premise: In this paper, we propose a peer-to-peer business model for drug discovery that democratizes the drug discovery process and reduces drug prices by cutting the intermediaries between biomedical researchers and future patients. Note that in this market microstructure, the underrepresented group can take advantage of medical advances by selling their data for research.

Approach: We devise a market microstructure in which a group of project managers, who are usually "star" scientists or CEOs of biotech firms, will select individuals at disease risks and researchers, raise funds by selling non-fungible tokens (NFTs) based on their future patents, and control risks by the rating system, due diligence, and financial engineering. Employing a signaling game-theoretic mechanism, our analysis not only elucidates how the stakeholders strategically interact in this market using deception, adverse selection, and moral hazards, but also how to tame their interactions to improve the overall performance. In particular, we suggest and rigorously evaluate an embodiment built on a scalable implementation of NFTs.

Results: Using extensive simulations, we show that in the NFT megafund, both senior and junior tranche investors get their principals fully repaid 99.9 percent of the time.

Conclusion: This market micro-structure can help reduce health disparity in the following three ways. First, by participating in the drug discovery process, the underrepresented population can accelerate drug discovery for diseases unique to themselves. Historically, such diseases are understudied due to a lack of funding and resources. Second, cutting out the middleman can significantly reduce drug-development costs, which will increase access to medicine. Finally, retail investors can also benefit from investing in drug discovery because the risk associated with the NFT is managed down to the level of debt.

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Consistency: As a disruptive technology, blockchain has created a lot of challenges and uncertainties for the economy and society alike. This research provides a framework to realize the potential of blockchain and non-fungible tokens to democratize the drug discovery process and reduce health disparity, while controlling their risks using rating system, due diligence, and financial engineering, which is consistent with the purpose of this journal.

Keywords: blockchain, cancer megafund, economics of science, financial engineering, non-fungible token (NFT), peer to peer

JEL Classification Codes: G32, I1, L65, O3

INTRODUCTION

The COVID-19 pandemic has unequally affected many racial and ethnic minority groups who face multiple barriers to accessing health care. Lack of insurance, transportation, child care, or ability to take time off work are just some of the disparities that keep them from going to the doctor. In fact, the pandemic has exposed the longstanding structural drivers of health disparities, such as housing, physical work environment, social support, stress, nutrition, and physical activity, which interlink with class, ethnicity, gender, education level, and other factors (see Chowkwanyun and Reed 2020; Lopez, Hart, and Katz 2021 for detailed studies and data). This increasing awareness of health disparity has prompted widespread calls for fair access to health care system in a post-COVID era (e.g., CDC's guideline on health equality[1]).

This paper focuses on the business model of drug discovery and how it should be adjusted to reduce disparities in health care. The unequal access to needed but patented, expensive medicines exacerbate existing disparities among disadvantaged populations (e.g., Essien, Dusetzina, and Gellad 2021) has been well documented. Take cancer drugs for example. The recent breakthroughs in genetic therapy beg for urgent and fundamental changes in the health care financing system. Genetic therapy, as constrained by its perceived small market sizes, is expected to raise the already sky-high prices of specialty drugs, thus aggravating already frustrated patients (e.g., Stern, Alexander, and Chandra 2017; Workman et al. 2017). For example, the first $1 million *per injection* genetic therapy, Glybera, was withdrawn from the market because of a lack of demand (Senior 2017). The $84,000-per-treatment drug, Sovaldi, is not covered by many insurers until the patient develops severe liver damage (Kardish 2014). Such high drug prices are tolerated without a serious debate because, according to the conventional wisdom, they are necessary for medical innovation, which is expensive, time-consuming, and risky in comparison to other technologies. However, if we look at the workforce behind every medical innovation, namely, the biomedical scientists, their research environment has been steadily deteriorating during the past thirty years, as the spending on prescription drugs increased by an order of magnitude. For example, during 1980–2016, the percentage of biomedical PhDs who found research-related positions has dropped from 65 to

[1]https://www.cdc.gov/coronavirus/2019-ncov/community/health-equity/race-ethnicity.html

55 percent,[2] the average age of a biomedical scientist who received his or her first funding from National Institute of Health (NIH) increased from 36 to 42, and the success rate for a research proposal to get NIH funding dropped from 40 percent to below 20 percent. In addition, a typical journey for a creative biotech entrepreneur in translating a discovery to commercialization remains full of unusually large number of hurdles (investment, due-diligence, IP protection, etc.)—resulting in an experience, commonly described by the practitioners as a “Valley of Death” (e.g., Alberts 2018; Fernandez, Stein, and Lo 2012; Kahn and Ginther 2017; Levitt and Levitt 2017). These findings are alarming because the drug discovery business model, in its simplest form, is an implicit social contract between patients and researchers. The goal of such contracts is to motivate researchers to find a cure for patients and get rewarded for their work. All the other stakeholders in the health-care industry—government, patient advocacy groups, pharmaceutical companies, and insurance companies—are supposed to make this process more efficient and affordable, and not to make it more complicated, opaque, and ultimately, burdensome to both patients and researchers.

Well aware of the flaws of current business models for drug discovery, some biomedical research labs start to auction non-fungible tokens (NFTs) based on their past scientific discovery to raise funding (Jones 2021). An NFT is a unit of data stored on a blockchain that certifies a digital asset to be unique and therefore not interchangeable. The distinct construction of each NFT has the potential for several use cases. For example, they are an ideal vehicle to digitally represent physical assets like real estate and artwork (Whitaker 2019; Whitaker and Kräussl 2020), or intellectual assets like patent and medical data. Because they are based on blockchains, NFTs can also be used to remove intermediaries, simplify transactions, and connect innovators with customers. Public attention toward NFTs has exploded in 2021, generating 23 billion dollars in trading volume in 2021, hundred times more than that in 2020.[3]

Theoretically, NFT has the potential to democratize the drug discovery process that has traditionally benefited pharmaceutical companies, which are the intermediaries that stand between biomedical researchers and future patients. However, it does not necessarily reduce health disparity. Indeed, empirical studies aiming at characterizing properties of the NFT market show that the structure of the the NFT co-ownership network is highly centralized and small world–like. After analyzing 6.1 million trades of 4.7 million NFTs using 160 separate cryptocurrencies between June 2017 and April 2021, Nadini et al (2021) found that “the top 10 percent of traders alone perform 85 percent of all transactions and trade at least once 97 percent of all assets.”

To fulfill NFT’s promise of reducing health disparity, we devise a market micro-structure in which a group of project managers, who are usually “star” scientists or CEOs of biotech firms, will select individuals at disease risks based on a their medical data (e.g., a shared genomic mutation in the individuals that is targeted for therapeutic intervention) and researchers based on their skills, repu-

[2]Research-related jobs are defined as tenure-track positions in universities or research positions in pharmaceutical industry.

[3]https://www.forbes.com/sites/ninabambysheva/2021/12/23/nfts-generated-over-23-billion-intradingvolume-in-2021/?sh=57b0900f5f0a

tation, and network. The project managers raise funds by selling NFTs based on their future patents (henceforth *bio-coin*) and control risks by a rating system, due diligence, and financial engineering. Note that, in this market micro-structure, underrepresented groups can take advantage of medical advances by selling their data for research. The investment in diversified translational innovation also improves the liquidity of the underlying fungible tokens in a Keynesian manner. In fact, a few companies have already been experimenting with ways for customers to sell genomic data on blockchain marketplaces (DeFrancesco and Klevecz 2019). For example, Nebula Genomics uses blockchain technology to allow 15,000 people whose entire genomes it has sequenced to grant temporary access to their data to specific users (such as biotech startups searching for links between genes and diseases). This market micro-structure can help reduce health disparity in the following three ways. First, by participating in the drug discovery process, underrepresented population can accelerate drug discovery for the diseases that are unique to themselves—historically such diseases are understudied due to lack of funding and resources. Second, cutting out the middleman can significantly reduce the drug-development costs, which in turn will increase the access to medicine. Third, retail investors can also benefit from investing in drug discovery because the risk associated with the NFT is managed down to the level of debt, as our simulation shows in “Return to the Investors.”

This paper has been partially motivated by research from Andrew Lo and his collaborators on a cancer megafund (e.g., Chaudhuri et al. 2018; Das et al. 2018; Fagnan et al. 2013; Fagan et al. 2015; Fojo and Lo 2016; Siah et al. 2019; Wong et al. 2018). However, it is worth noting parenthetically that the organizational structure of this decentralized megafund is fundamentally different from that of the megafund proposed by Fagnan et al. (2013) (henceforth, *centralized megafund*). In the centralized megafund, the fund managers need to optimize decisions of capital structure, through the buying and selling of compounds for each experiment, as well as the hiring and contracting of researchers in each stage of the drug development. The possibility of a misalignment of interests between fund managers and investors—one of the primary reasons behind the 2007–2009 financial crisis—could significantly reduce the profitability of such a megafund (Yang, Debonneuil, and Zhavoronkov 2016). The megafund would overcome this concern by using a decentralized, transparent, and market-based solution for drug development. All the activities are direct contracts between investors (potential patients) and researchers using the blockchain and smart contract technology. By avoiding a central authority governing the market and other transitional institutions, it avoids non-transparency and deception associated with market manipulation. It also globalizes the system and encourages scaling with liquidity.

The paper also builds on the earlier work of Yang, Debonneuil, and Zhavoronkov (2016) on a cancer megafund with embedded “lemon” projects in the information asymmetric structure. This paper improves on that work by further reducing information asymmetry, deceptive behavior, and thus overall risks that may derive from the megafund itself. Specifically, for the bio-coin to be acceptable to all investors, scientists, and future patients (individuals at disease risks), we need to ensure that all participants in the drug development agree on the value of this NFT. The drug-development process is highly experimental in the sense that its success rate depends on the talents, stamina, and perseverance of scientists, and its outcome cannot be evaluated solely by computer models *in silico*. Therefore, some additional institutions to facilitate the drug discovery process and honor the commitment by the bio-coin are also needed. For example, a reputable rating agency will significantly reduce the informational asymmetry between future patients (individuals at disease risks) and the scientists. In the rating agency, each proposal of a scientific project requires deploying a data science algorithm (machine learning, systems biology, disease modeling, etc.) to verify that it has a solid theoretical and experimental foundation. In addition, the cost of due diligence has diminished exponentially because of the significant breakthroughs in systems biology, synthetic biology, high throughput lab-on-chip, and omics technology have been making.

A real-life example of such a rating agency is the Operation Warp Speed committee for U.S. COVID vaccine development. This committee funded 8 projects out of 250 vaccine candidates, and 6 of these 8 vaccine candidates have been approved by FDA as of today, which shows that it is possible to significantly increase the success rates of investment by conducting careful due diligence. Other examples are online analysts for initial coin offerings (ICOs). According to Lee, Li, and Shin (2021), analysts can predict the success rates of an ICO with high accuracy.

The paper is organized as follows. "Institutional Background" first explores why the cooperation in biotechnology research is rapidly breaking down. Next, "New Approaches" elaborates on how the bio-coin megafund can help solve this problem. "Description of the Equilibrium" presents the nature of financial returns to future patients (individuals at disease risks), scientists, and investors in our new incentive systems, as well as empirical analysis via simulation. The conclusion follows with a succinct discussion on the benefit of our approach.

INSTITUTIONAL BACKGROUND

This divergence between health-care spending and innovation is attributed to the central institutional feature in the current health-care market: the demand side of medical innovation does not match the supply side directly (Ellis and McGuire 1993). The demand of medical innovation comes from the fundamental need of each individual to insure against the significant health and monetary losses caused by illness (Lakdawalla, Malani, and Reif 2017; Philipson and Zanjani 2014). All these needs are then pooled, in the form of taxation and insurance premiums, respectively, by the government and insurance companies and redistributed, in the form of research funds and payment to prescription drugs, to the supply side of medical innovation–research institutions, biotech, and pharmaceutical companies. The drawback of such a centralized system, like most other centralized systems, is that it blocks the accurate information flow in the feedback loop for each individual to impact the price and quality of health-care products, thus opening doors for "price-gouging" by pharmaceutical companies and inefficiency in capital allocation as described above. As our knowledge about the linkage between genome and diseases keeps on evolving, the potential conflict of interests between the centralized authority and the general public may eventually harm the patients' welfare. For example, although testing a patient's whole genome sequence for predictive biomarkers is crucial for personalized treatments, it may negatively affect a person's insurance coverage and life insurance premium; therefore, (potential) patients are reluctant to make the best use of these tests. A transparent and decentralized health-care financing system, where the drug prices are set at market equilibrium and capital is allocated to meet the real-time demand, is a necessary complement to our current health-care financing system.

Figure 1 compares the current health-care financing models with the peer-to-peer model. In the current health system, there are four stages for each biotechnological research: (1) Funding; (2) Innovation and research; (3) Clinical trials and regulatory approval; (4) Pricing and marketing. Based on these stages, we categorize all the current research processes into two major approaches:

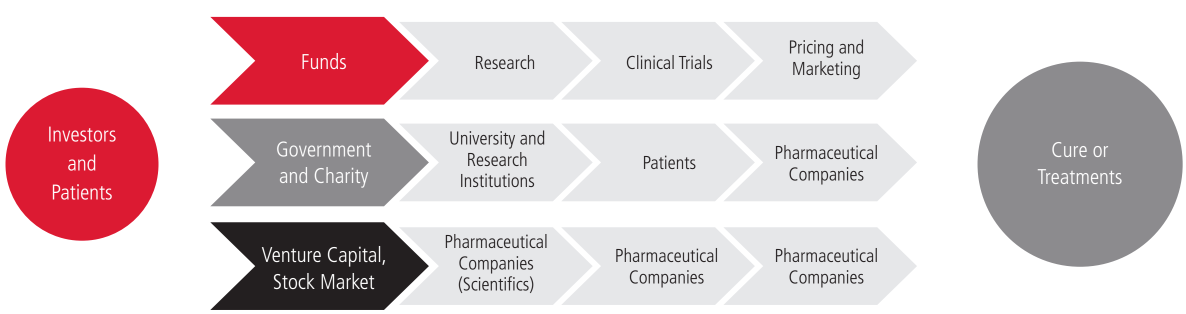
- Not-for-profit approach: Government agencies (or charity and other public organizations) collect funds from taxpayers (or the general public), and then distribute funds to scientists in the university labs or research institutions based on the peer-review process. When scientists make a breakthrough, they either start up an enterprise through a technology transfer office or they license it to pharmaceutical companies.
- Market approach: Pharmaceutical companies collect funds from venture capitalists or the capital market and hire scientists to work on promising projects. If a drug is approved by FDA, companies price it and sell it in the market or to hospitals.

In both of these approaches, participants from each stage usually have conflicts of interest, leading to fragmented strategies and agendas, which stifle information sharing across research teams necessary to advance treatments and cures.

Specifically, the not-for-profit approach suffers from the following three problems. First, government or non-profit organizations end up inefficiently allocating resources. For example, politicians may steer taxpayer's money away from drug development to serve their interests. As a result, under-investment is always an issue for not-for-profit drug development. Second, the interests of scientists and patients are not fully aligned. Purely academic competition among

FIGURE 1. Stages of Traditional Biotechnology Research

The current business models struggle with various forms of adverse selection, deception, and moral hazards, which result from information asymmetry, exacerbated by misaligned utilities, lack of a community wide social norms, and enforceable complete contracts.



scientists, while beneficial in basic science research, prohibits them from sharing research results transparently and only a small percentage of NIH-funded medical research yields positive results that end up in publications. Third, the drug price is determined by pharmaceutical companies, therefore there is no control by the taxpayer or patients (who through charity invest their money in the first place) to interact with the other key players rationally but strategically.

Although the market approach is more efficient in allocating resources, pharmaceutical companies may take advantage of its inherent information asymmetry to maximize corporate profit by charging high drug prices for the patients. In addition, they may only focus on disease groups that promise blockbuster returns and leave many rare diseases untreated. Powerful pharmaceutical companies also hold patents, trade secrets, know-how, copyright, etc. for processes associated with actionable biomarkers and molecules. They can charge significant licensing fees to researchers who use or work on these intellectual assets, imposing barriers to information sharing within the drug-development community. Thus, for instance, while personalized therapies are touted as the future of biomedicine, it is practically impossible to motivate a cohort to participate with their genomic data, as it will only deliver mostly equivocal, uninterpretable, or nonactionable biomarkers, but not much else.

NEW APPROACH

We propose to use bio-coin and associated smart contracts to integrate all the stakeholders into an interactive and rational system. In this way, the incentives among different participants are expected to be better aligned and a socially more attractive equilibrium can be achieved.

We formulate it as a principal-agent problem, in which future patients or individuals at disease risks (the principal) delegate the scientists (the agents) to search for a solution to the targeted disease. Scientists have private information about the distribution of potential outcomes and their abilities (adverse selection), as well as the efforts they put into researching (moral hazard). As has been documented by many researchers in the economics literature (Ulbricht 2016), the scientists will not work in the best interest of the future patients (individuals at disease risks).

Before we go into the contract details, we need two additional institutions: a megafund (with blockchain) to ensure that future patients (individuals at disease risks), investors, and scientists all believe that the bio-coin has value (see Figure 2) and a secondary market (see Figure 3) to ensure the liquidity of this bio-coin.

Details of the Bio-Coin Megafund

The megafund operates as follows:

Propose Research Questions: Publicly post different research questions and requests for proposals, soliciting globally a diverse set of scientific ideas, relevant to the problem. Potential researchers can log on to the megafund's website, find the page(s) that matches their area of expertise, peruse chal-

FIGURE 2. Bio-Coin Megafund

The megafund tames the information asymmetry with flows of information balanced by reciprocating flows of obligations and rights (via investments and smart contracts). Furthermore, it seamlessly includes all stake-holders: patients, researchers, investors, and regulators.

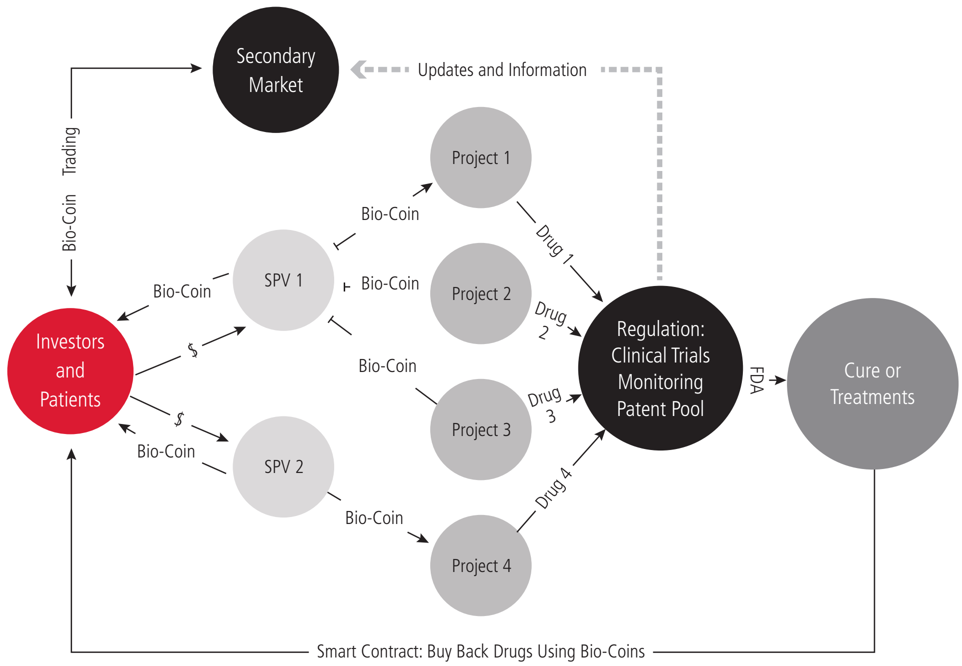
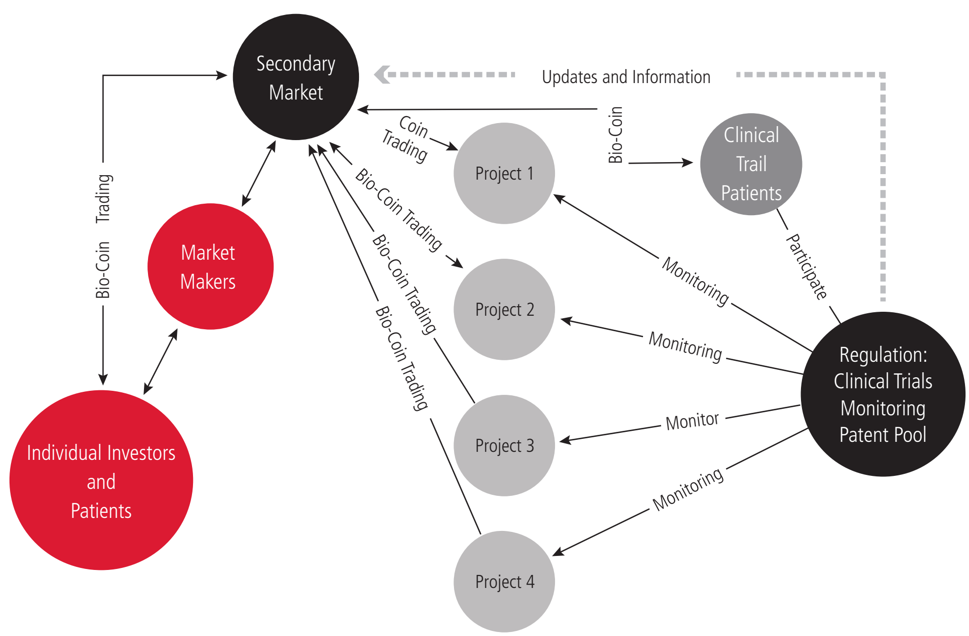


FIGURE 3. Secondary Market of Bio-Coin

The secondary market brings liquidity by inviting additional market participants, who may have access to better informatics (e.g., systems and synthetic biology) for monitoring, pricing, and arbitraging.



lenges to be solved—usually with an award of bio-coin attached—review others' contributions, download computerized tools, and start working toward contributions of their own. As they progress, they can timestamp their findings in the blockchain, discuss their insights in online forums, or propose new challenges. Over time, the better proposals will gain authority and select the de facto leaders of their research community.[4] The megafund uses this step to identify potential research projects to be funded.

Designing Special Purpose Vehicles (SPVs): The megafund designs different SPVs to meet the market demand for biomedical research. For example, for cancer research, some investors may consider immunotherapy approaches to be the most promising, while other investors prefer small cytotoxic molecules approaches. It can also encourage investors to set up their SPVs under the megafund's supervision.

Due Diligence: The megafund will pre-screen and select proposals from *step one* into corresponding SPVs. The proposals of scientific projects thus require deploying a data science algorithm (e.g., machine learning, systems biology, disease modeling, etc.) to verify that it has a solid theoretical and experimental foundation. This mechanism will reduce the risk by costly signaling to curb deception due to information asymmetry (lemon market). In addition, the cost of due diligence has diminished exponentially because of the significant breakthroughs in systems biology, synthetic biology, high throughput lab-on-chip, and omics technology have been making. Altogether, this step can significantly increase the return of this megafund (e.g., Yang, Debonneuil, and Zhavoronkov 2016).

Organizational Structure: The organizational structure of all the biotechnology research in one SPV follows the mission-directed approach used in the Defense Advanced Research Projects Agency (DARPA). DARPA is a small, relatively flat organization with only one level of management between the program managers and the director of the agency. Projects, program managers, and even the agency director rarely last more than 3 to 5 years, and there are seldom renewals. This constant flux of programs, program managers, and directors lead to a rapid generation of new ideas. Each project is managed by a proactive program manager, and quality performance is rewarded with increased funding. The relationship between each group is both competitive (because they need to compete for funds) and cooperative (because of the interdisciplinary and mission-driven research environment) (e.g., DARPA 2016).

NFT Auction: Calculate the expected risk and return for each SPV and design different tranches (e.g., Fagnan et al. 2013). Sell the bio-coin NFT that represents different tranches to the capital market. By avoiding a central authority governing the market and other transitional institutions, it avoids non-transparency and deception associated with market manipulation. It also globalizes the system and encourages scaling with liquidity.

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[4]According to the literature on open source drug discovery, two components are needed for any opensource question to get momentum: 1) the proposed question must be well-defined and able to be judged fairly; 2) It's also important for an impartial expert in the field to act as a convener and nurture the emerging community.

Cash Reserve: Because it may take several years before its investments begin generating revenues, capital raised from the ICO will be set aside as an initial cash reserve to fund clinical trials for its portfolio of compounds during the life of the transaction. These reserves will also ensure that timely payments of interest can be made on the research-backed obligations.

Staging Finance: Scientists accept a smart contract from the megafund (see “Return to the Researchers” for the details of smart contracts). They will get funds in the form of bio-coin if they meet a milestone. They then exchange for capital using this bio-coin in the secondary market. All the financing decisions, selling and buying compounds decisions, as well as hiring or firing employee decisions are made by the scientists at the project level. Financial information will be recorded on the blockchain to help investors monitor.

Regulation: In our current system, it is the pharmaceutical companies that sponsor clinical trials. This method can potentially cause a conflict of interest (Lexchin et al. 2003). In our approach, it is the megafund that employs different monitoring and drug-testing techniques, which include computational simulation, animal, organoid, or *in vivo* cell line-based experiments, and clinical trials. They test the outcome from each stage of the scientific projects and disclose all the information to the public in real-time. Regulation avoids non-transparency by allowing the community to learn collectively from each failure. Based on the published evaluation of the research progress, investors update their expectations of the risk and return from each SPV and trade them in a secondary market. Patients who participate in clinical trials can also be compensated by bio-coin.

Patent Pool: Pool all the patents and research findings and share them freely within the system, avoiding information asymmetry due to patent trolling and mutual blocking.

Details of the Bio-Coin Exchange Market

In the secondary market, the demand side of this bio-coin includes:

Patient Activists: Many patient activists, usually the family and friends of a patient, have already come forward to fill the research gap and look for a cure for their loved ones. For example, Kim and Lo (2016) report a case study of an early-stage life sciences company, Solid Biosciences, founded by a father of a young boy with a rare genetic disorder (Duchenne muscular dystrophy [DMD]). The bio-coin megafund provides a platform for patient activists to set up their campaigns.

Future Patients: Investors who suffer from, or carry a high risk of getting, a certain type of disease. Diagnostic tools can identify such patients accurately.

Charities: Charities can buy bio-coin and distribute them among patients.

Market Makers: Pharmaceutical companies, health insurance companies, public health organizations (e.g., CDC) may join the exchange market as market makers or arbitragers, namely they asynchronously buy a big block of this bio-coin based on their estimation of the demand and sell it to future patients. All their participation can improve the market efficiency of this NFT.

The supply side of this market includes:

Researchers: Scientists can get funded after due diligence/reviews and can convert their bio-coin into cash to pay for the lab research.

Investors: Investors can plan their investment strategies based on their disease profile. For example, they may invest in BRCA1 (breast cancer biomarker) research when they are young and sell their bio-coin in the secondary market when they are aging, to exchange for bio-coins for another disease such as neuro-degeneration, based on a recent genetic analysis.

All these market participants create time-varying demand and supply of bio-coins, affecting the liquidity and the price of this NFT.

DESCRIPTION OF THE EQUILIBRIUM

To see that the new equilibrium improves the social welfare, we need to convince ourselves that the total return to future patients (individuals at disease risks), scientists, and investors is improved relative to what can be obtained in the existing market structure, and all parties individually can strategize rationally to propel the drug discovery process forward.

Return to the Future Patients (Individuals at Disease Risks)

The benefits to future patients (individuals at disease risks) are straightforward. Under the current medical system, the future patients (individuals at disease risks) receive nothing for sharing their personal health data or for investing through charity or taxes, while in the proposed new system, they get some ownership of the final product. This market will generate significant returns for the future patients (individuals at disease risks) if the research is successful and also give them some control rights on the pricing of the pharmaceuticals.

Return to the Researchers

In our approach, more productive researchers will get much more research funds and higher compensation than the current system. There are three goals when we design the new funding system: (1) More innovative, efficient, and productive researchers will get more funds; (2) The researchers will be paid based on their performance, therefore the return to researchers with breakthrough discoveries under the new system will be significantly higher than the current system; (3) The researchers are encouraged to take risks. In other words, they won't be punished for failure when trying innovative approaches.

To design a funding system with these features, we need a better understanding of the following two questions: (1) What is the production function of knowledge? (2) What is the best way to motivate researchers? These are questions that have been studied for decades, yet no consensus has been reached.

Here we borrow some recent development from the mechanism design literature and present a new funding scheme that can generate better returns to the researchers and investors than our current system.

Recall that we frame the question as a principal-agent problem, in which investors (the principal) delegate the scientists (the agents) to search for a solution to the targeted disease. Scientists have private information about the distribution of potential outcomes and their abilities (adverse selection), as well as the efforts they put into researching (moral hazard). They can choose between two different approaches to finish the job: one is a routine approach, and the other is an experimental approach. We then combined the findings from the dynamic mechanism design literature (e.g., Halac, Kartik, and Liu 2016; Ulbricht 2016) and propose a new mechanism as follows:

1. At the creation of each SPV, scientists submit their research proposals to the megafund. This research proposal will include estimates for deadlines, measurable milestones, and the budget needed for each milestone.
2. All the research proposals are analyzed by the megafund and ranked based on the past performance of the scientist,[5] the feasibility of the research approach, correlation of this approach to other approaches, and its budget. More importantly, the megafund may also need to understand the interdependence among the proposals and the nature of coordination, cooperation, and competition that it entails.
3. An approved research project is funded under a vesting schedule associated with a bio-coin account. A smart contract, imposed on the account, pays the scientists as determined by the research proposal. That is, bio-coin for the next stage of research is paid to the scientist if and only if the targeted milestone at the current stage is met within the predetermined time frame.
4. The budget has an option-like feature: the amount of bio-coin paid at each stage is determined by the initial price of the bio-coin, or the current price of bio-coin if it is lower than the initial price, to meet the proposed budget. In other words, if the price of the bio-coin appreciates, the scientists will enjoy a higher value than their proposed budget; if the price of the bio-coin depreciates, the scientists still get their proposed budget.
5. For projects that are terminated early because of failing experiments or missing a milestone, the remaining unspent bio-coin are redistributed among the other ongoing projects. In this way, the successful projects are rewarded not only by the appreciation of the bio-coin but also by the increasing amount of their bio-coin budget. This structure is reminiscent of DARPA's program continuation scheme with hurdles.

As we can see from the structure of the smart contract, the return to researchers depends on their reputation in the megafund, the price of the bio-coin, their effort at each stage, and their peers' efforts. This type of smart contract can address the following information asymmetry problems:

Adverse Selection: Since scientists are paid for their long-term performance, their motivation of producing "lemon projects" is minimized. As in the

[5]In the megafund, each scientist is ranked based on their past performance, skills, and talents, which is continuously updated in real time.

game-theoretic literature, a "lemon project" refers to the situation where a scientist has deceptively concealed his lack of skill or the infeasibility of the proposed project by overstating his qualifications or by justifying the project with fraudulent, non-reproducible results, respectively. These projects can only meet a few initial milestones and their fund will be shut down as soon as the flaws are detected. Such an outcome will hurt the scientist's reputation and significantly reduce their chances of acquiring future research funds from the megafund.

Risk-Taking: The option setting of the budget ensures that the scientists are protected from the downside risk in research and will be willing to take risky actions. First, if any research succeeds in the pool and the price of bio-coin appreciates, then the fund for all the other scientists in the pool will also be increased. Therefore the compensation to scientists not only depends on the outcome of his experiment but also on the SVP's pool of other experiments. Second, if many research projects in the pool fail, the secondary market may irrationally depreciate the bio-coin. The megafund will guarantee that other scientists' projects are still properly funded. In this way, the megafund ensures that all scientists put proper efforts into their respective projects to avoid a contagious default of the SPV.[6]

Moral Hazard: The design of the fund also ensures that scientists who make a breakthrough in their research will be rewarded proportionately. First, if any compound in the system goes to next phase,[7] the price of the bio-coin will jump significantly. Second, funds from failed projects will be redistributed among the surviving projects in their funds. Suppose just one drug gets FDA approval in an SPV, then the team that discovered this drug will get the highest amount of bio-coin. It is the same amount of bio-coin had the team conducted all the experiments in the SPV on their own.

Free Riding: Note that the smart contract has two opposite effects on the scientists' motivation. On one hand, the long-term income induced by their reputation motivates them to put as much effort as they can (career concern); on the other hand, the fund they get is a function of the price of the bio-coin, which depends on their performance. However, because the outcome of the megafund (or the price of bio-coin) is a joint effort of all the scientists in the portfolio, scientists may want to "free ride" and put less than assumed efforts into research. The terms and structures of the smart contracts need to be carefully designed so that the career-concern motivations dominate the free-ride incentives.

Return to the Investors

Compared to collateral-backed securities, research-backed obligations have three major shortcomings: (1) There are significant variations in their cash flows; (2) The correlation among research projects are highly correlated as researchers tend to collaborate; (3) The patent valuation distribution is highly skewed and

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[6]This type of correlation is difficult to calculate in advance. To make things worse, in foreseeing this possibility, investors may dump the bio-coin even for a few bad outcomes and undervalue the bio-coin, further disappointing scientists. This spatial cycle will eventually cause the secondary market to collapse. Therefore the insurance of megafund is necessary to stabilize the secondary market.

[7]There are seven phases for drug development.

difficult to calculate. As such, we utilize a variety of approaches to calculate this return.

One approach is to examine the existent practices to quantify the risk and return of such investment. The organizational structure of this novel bio-coin megafund differs fundamentally from that of the centralized megafund proposed by Fagnan et al. (2013). In Fagnan et al. (2013), all the decisions are made by a fund manager (or managerial team), while in our approach, most of the financial and research decisions are made at the project level and the fund manager (or managerial team) is only to set all the rules and disclose information in a timely matter. Detailed information on the model parameters can be found in the Appendix.

Simulated Returns of Bio-Coin Megafund

Compared to the centralized megafund, the bio-coin megafund can improve the return to investors by reducing the following costs.

1. Management costs: Blockchain technology with its proof-of-work cost signaling can significantly reduce the costs for investors to collect unadulterated reliable information and for managers to monitor their employees. Smart contracts can save costs for law enforcement of potential patent violations or contract breaches. In our simulation, we assume that the management fee of the bio-coin megafund is only one-tenth of the megafund using a traditional organizational form. This number is based on (Munos 2006), in which the author found that the management costs for an average open-source initiative are about one-tenth of the management costs for running a pharmaceutical company.
2. Higher success rate: Due diligence approaches can reduce the chances of funding lemon projects, which will improve the possibility that targets progress from preclinical stages to clinical trials. In addition, significant breakthroughs in systems biology, synthetic biology, high throughput lab-on-chip, and omics technology have been making the cost of due diligence diminish exponentially. Moreover, sharing patents in the megafund can also stimulate follow-up research. We estimate that the resulting probability of success in the bio-coin fund is about 30 percent higher than that of traditional megafund, which is based on Williams (2010) and Yang, Debonneuil, and Zhavoronkov (2016).
3. Cost of dead-end research: Sharing dead-end information can avoid unnecessary duplications in the way research is carried out. Based on Akcigit and Liu (2014), we estimate that it will reduce drug-development costs by 20 percent.

To illustrate the profitability of the bio-coin megafund, we simulated a bio-coin megafund that generates similar cash flows as in the centralized megafund (see the Appendix for technical details).

Table 1 contains a comparison of the results for 1,000,000 simulated paths for the megafund as in Fagnan et al. (2013) shown in column (A) of Table 1, megafund with lower management fees in column (A1), megafund with systems biology due diligence and patent pooling in column (A2), megafund with infor-

TABLE 1. Cancer Megafund Simulation

Summary statistics of cancer megafund simulation for the megafund as in Fagnan et al. (2013) shown in column (A), megafund with lower management fees in column (A1), megafund with due diligence and patent pooling in column (A2), megafund with information sharing in column (A3) and finally, our bio-coin-megafund (bio-coin) in the last column, each capitalized with $3 billion of equity over seven and a half years, as well as $1.25 billion of senior debt and $0.75 billion of junior debt for a total capitalization of $5 billion. We also add a guarantee with a maximum face value of $1 billion.

Simulation Variable or Summary Statistic	Megafunds				
	A	A1	A2	A3	Bio-Coin
Parameters					
Management fee (%)	25	2.5	25	25	2.5
Probability from preclinical to Phase I	0.345	0.345	0.517	0.345	0.517
Drug-development cost	x	x	x	0.8*x	0.8*x
Simulation results					
Number of compounds to reach Phase II	99.0	99.4	99.0	105.7	105.8
Liabilities					
Senior tranche (USD million)	2,000	2,000	2,000	2,000	2,000
Junior tranche (USD million)	750	750	750	750	750
Equity (USD million)	2,250	2,250	2,250	2,250	2,250
Guarantee (USD million)	1,000	1,000	1,000	1,000	1,000
Equity tranche performance (%)					
Average annualized return on equity	8.9	9.3	8.7	17.7	18.3
Prob. (return on equity < 0)	21	19.6	20.9	4.2	3.1
Prob. (return on equity > 0.05)	69	70.3	68.1	90.7	92
Prob. (return on equity > 0.15)	41	43	40.8	64	82
Debt tranches performance					
Senior tranche: PD, EL (bp)	< 0.3,< 0.1	< 0.1,< 0.1	< 0.1,< 0.1	< 0.1,< 0.1	< 0.1,< 0.1
Junior tranche: PD, EL (bp)	39, 15	36, 11	37, 13	< 0.1,< 0.1	< 0.1,< 0.1
Guarantee cost (2 percent discount rate)					
Prob. (cost of guarantee > 0) (%)	2.0	2.03	2.04	0.6	0.2
Average cost of guarantee (USD million)	10	9.49	9.71	0.1	0.52
98th-percentile draw on guarantee (USD million)	17	9.4	18	0	0
99th-percentile draw on guarantee (USD million)	429	378.8	449	0	0

mation sharing in column (A3), and finally, our bio-coin-megafund (bio-coin), each capitalized with $3 billion of equity over seven and a half years, as well as $1.25 billion of senior debt and $0.75 billion of junior debt for a total capitalization of $5 billion. We also add a guarantee with a maximum face value of $1 billion.

The column labeled "bio-coin" indicates that our approach is significantly more profitable and stable than transitional methods. In the bio-coin megafund, both the senior-tranche investors (with an annual coupon of 5 percent) and the junior-tranche investors (with an annual coupon of 8 percent) get their principals repaid in full 99.9 percent of the time, which is comparable to historical default rates of the highest-rated bonds reported by Moody's and Standard & Poor's. Equity-tranche investors received an average annualized return of 18.3 percent. In 82 percent of the simulated sample paths, the average annualized return for equity exceeded 15 percent, versus only about 41 percent for the case of the megafund of transitional organizational form. In addition, the expected cost of the guarantee to the provider is only $0.52 million, much smaller than a $10 million loss in the traditional megafund. It suggests that the bio-coin megafund is more stable than traditional forms.

CONCLUSION

Since all the participants in the system are compensated by the bio-coin, which is only valuable when a drug is developed, the interests of different participants are aligned. In addition, the allocation of capital and resources is more efficient because of the market mechanism that is used to decide the value of the bio-coin and allow it to be traded in real time. Because a reputable megafund can support high quality, due diligence, and regulated processes, the return from biotechnological research is quite lucrative, and the funds which flow into biotechnological research are likely to naturally increase.

For Investors: Investors get a diversified portfolio of drug-development projects. Since the risk in drug development is less likely to be correlated with other established risks in the market, these bio-coin enrich the investors' investment set. The secondary market also provides liquidity for the bio-coins. In addition, we reduce the possibility of fund managers manipulating the fund and thus prevent a financial crisis from happening.

For Patients (or individuals with disease risks): Individuals can get the bio-coin for future treatments (for a disease) either by investing directly or by participating in clinical trials, sharing their DNA sample or electronic health record (EHR), and so on. Even when the specific clinical trials involving them may fail, they can still benefit if other drugs in the SPV succeed. This feature allows the general population to hedge the health risk that they are likely to face in their lifetime.

For Scientists: Since scientists are compensated on a market-orientated approach, their research is more directly linked to the market demand, which helps them to conduct more applied and efficient research. For example, when searching for potential projects to work on, scientists can take the market prices of bio-coin for different drug-development projects into consideration and are more likely to work on projects of high demand from the investors. Moreover, the megafund provides a community that incentivizes scientists to share their ideas, which also leads to more cooperation across different research teams. In addition, instead of focusing on just only one drug-development project, the scientists now also have a diversified portfolio, which hedges their risks too. Such a hedge can ease their short-term concerns and make them more far-sighted and less deceptive.

Our approach is closely related to open-source biotechnology research, but with the help of bio-coin, NFT, blockchain, and smart contracts, the research projects in the megafund are conducted in a more controlled way and hence can guarantee a solid return to investors. With the signaling function of the bio-coin and proof-of-work mechanisms for costly signaling, resources are allocated more efficiently, and hence provide the foundation for cooperation and trust among future patients (individuals at disease risks), investors, and scientists. Such a closed-loop system will be attractive to more participants than simple normative open-source biotechnology research.

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Appendix A: Simulation of Bio-Coin Megafund

The organizational structure of the centralized megafund (Fernandez, Stein, and Lo 2012) and the bio-coin megafund are fundamentally different. All the financing and monitoring decisions are made at the research project level. But to illustrate the profitability of the bio-coin megafund and make it comparable to the centralized megafund, we simulate a bio-coin megafund that generates similar cash flows as in the centralized megafund.

Specifically, we assume that all the research projects are identical and follow the same success probabilities and valuations as that of the centralized megafund. As a result, at the aggregated level, the financing mechanism, business structure, and cash flow could be very similar for these two structures. Namely, the objective of both megafunds (or the special purpose vehicles) would be to get cash flows from selling compounds at a different stage of drug development to satisfy the megafund's obligations to its bondholders and providing attractive returns to its equity investors.

There are five key components in our simulation:

1. Compound Valuation: Fernande et al (2012) estimate their distributional model of compound valuation based on the market value of the portfolios of drug compounds of public pharmaceutical companies. This would be the same approach when investors evaluate the bio-coin in the exchange market. Hence, we use their parameters and models in our simulation.
2. Transition Matrix: We also use the transition matrix of drug development from Fernande et al (2012) with one exception. For the possibility of targets making a transition from preclinical stages to clinical trials, we assume it is 30 percent higher in the bio-coin megafund than in the centralized megafund, because due diligence and patent pool in the bio-coin megafund can reduce the chances of funding "lemon" projects and encourages follow-on innovations, which leads to further improvement. Our estimation is based on Williams (2010) and Yang, Debonneuil, and Zhavoronkov 2016).
3. Development Costs: Within each research project, scientists try to optimize the profits by minimizing the costs. The types of payments made by the research project during its life include the following:
   - Start-Up Expenses and Purchases. The scientists will exchange bio-coin for upfront and milestone payments as well as funding Research and Development (R&D) and clinical trials.
   - Ongoing R&D and Financing Expenses. Scientists will pay for ongoing R&D expenses of the portfolio assets during the life of the megafund. As part of this process, scientists may decide to sell some of their assets and engage in other corporate transactions to realize gains, meet funding needs, or for other strategic reasons.

   In the bio-coin megafund, because sharing dead-end information is compensated, unnecessary duplication of unproductive research can be avoided. Based on Akcigit and Liu 2014, we assume that this leads to a reduction by 20 percent of all the drug-development costs, listed above.

4. Management Costs: During each year, the special-purpose vehicle will pay salaries to its staff, fees to external service providers, and other operating costs that are part of the management fee. Fernande et al (2013) assume that this number is 0.25 percent of the total assets under management. Since blockchain technology can significantly reduce the costs for investors to collect information and smart contracts can save costs for managers to monitor their employees and law enforcement of potential patent violation or contract breach, we assume that the management fee of the crypto market megafund is only 0.25 percent of the total assets under management, which is one-tenth of the centralized megafund. This number is based on Munos (2006), in which the author found that the management costs for an average open-source initiative are about one-tenth of the management costs of running a pharmaceutical company.

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The Economic Worth of the Firm's Interorganizational Relationships in Acquisitions: A Social Network Perspective

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Abstract

Motivation: We treat the network position of target firms as a source of value creation in mergers and acquisitions (M&As), and intend to gauge the associated economic value.

Premise: We adopt the social network methodology to capture the target firms' network position and relate it to abnormal returns experienced by the acquiring firms on the announcements.

Approach: We use a sample of 728 completed acquisitions in the United States from 1990 to 2011 and employ social network analysis and event study methodology to conduct our analysis.

Results: We document that the stock market responds positively to the target's centrality. We also find that the combined centrality and the relative centrality of the acquiring firm and the target firm enhance the performance of a particular acquisition. Furthermore, the positive effects of the target firm's centrality on the acquirer's shareholder value creation are stronger when the acquisitions are related deals or the acquirer has prior experience in the target's industry.

Conclusion: This study offers a systematic analysis of whether and how a target firm's network position leads to the shareholder value creation of the acquirer. It demonstrates that the externally derived network position and resources of the target firm can influence the stock market's valuation of M&A deals.

Consistency: This study provides implications for practitioners with respect to how the acquiring firms assess the targets to create shareholder value in M&A transactions.

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INTRODUCTION

Mergers and acquisitions (M&As) are commonly used as a means for the acquirer to obtain and internalize resources and competencies possessed by the target firms. The Thomson Financial SDC Platinum (SDC) Mergers and Acquisitions Database has reported 126,000 completed acquisition transactions between 1995 and 2012 in the United States. In 2016 alone, the value of U.S. acquisitions reached $1.5 trillion (MergerMarket 2017). These trends suggest that M&As are a widely employed strategy for firms to maintain a competitive position and sustain growth. Through M&A transactions, the acquiring firm gains legal control over the target's assets and resources in an attempt to generate economies of scope, attain market power, explore growth opportunities, or broaden its portfolio of products and services (Haleblian et al. 2009).

Prior M&A literature mainly focuses on internally owned resources as a source of synergistic combination and value creation in M&As (Capron et al. 1998; Capron and Hulland 1999; Makri, Hitt, and Lane 2010; Puranam and Srikanth 2007; Uhlenbruck, Hitt, and Semadeni 2006). Recent research has emphasized network positions as potential resources that can create value for firms (Dyer and Singh 1998; Gulati 1998; Lavie 2006). Nevertheless, M&A research exploring the value creation of network positions is surprisingly scarce, and this paper attempts to fill this void in the literature. Specifically, we ask the following research questions: (1) How does the stock market value the target firm's network positions in M&A deals? (2) Under what circumstances does the stock market place a higher valuation on the network positions of the target firm?

The motivations of the study are three-fold. First, one important question in M&A research is how economic value is created for the acquirer (Haspeslagh and Jemison 1991; Hitt et al. 2001). Empirical evidence generally concludes that M&As do not enhance the shareholder value of acquiring firms (Agrawal and Jaffe 2000; Agrawal, Jaffe, and Mandelker 1992; Asquith 1983; Dodd 1980; Malatesta 1983). Studies of the combined bidder and target return document similar results. Even though M&As produce positive combined returns, the majority of those gains accrue to the shareholders of the target firm (Bradley, Desai, and Kim 1988; Carow Heron, and Saxton 2004; Healy, Palepu, and Ruback 1992). The shareholders of the acquiring firm, on average, experience neutral or negative returns (Bradley, Desai, and Kim 1988; Houston, James, and Ryngaert 2001), with some deals destroying value (Chatterjee 1992; Datta, Pinches, and Narayanan 1992; King et al. 2004; Moeller, Schlingemann, and Stulz 2004; Seth, Song, and Pettit 2000). Despite the insignificant returns generated for the acquiring firm, there exist considerable variance in the acquirer's performance. In some successful cases, acquisitions have generated profits ranging from 30 to 40 percent for the shareholders of the acquiring firm (Bradley, Desai, and Kim 1988). Understanding what accounts for the variation of acquisition performance can provide important implications for M&A practices. This study examines the source of value creation for the acquiring firm with a specific focus on the target's network positions and related contextual factors.

Second, research on the network positions for value creation is largely missing in M&A literature. Prior research treats interorganizational relationships as a means to gather information to cope with the uncertainty of M&A transactions. As M&A transactions are risky endeavors marked by great uncertainty, the acquirer can learn from other organizations through interorganizational ties, such as interlocking directorships and ties to acquisition advisors, in making M&A decisions. These interorganizational ties can affect the acquirer's decisions, such as the propensity to acquire (Beckman and Haunschild 2002), overall M&A activities (Lin et al. 2009) and the price paid for the target firm (Haunschild 1993; Haunschild 1994). Following the same logic of interfirm ties as a mechanism of uncertainty reduction, other studies examine whether the direct ties between the acquirer and the target (Porrini 2004; Zaheer, Hernandez, and Banerjee 2010) or their ties to a common third party (Rogan and Sorenson 2014) can alleviate the problem of information asymmetry in M&A transactions. Researchers also take the target's perspective and examine how the target's interorganizational relationships, such as ties with venture capitalists or alliance partners, affect M&A outcomes (Beckman and Haunschild 2002; Reuer, Tong, and Wu 2012). In these studies, the target firm's interorganizational relationships serve as a signal of firm quality that helps alleviate the information asymmetry between the acquirer and the target. While these studies have informed us how interorganizational relationships of the acquirer and the target respectively reduce uncertainty and drive M&A behaviors and outcomes, there is limited research on how the target's network positions affect M&A performance. Except for Hernandez and Menon (2017), no research has yet taken a network structural perspective and examined the performance implications of the target's network positions. Firms undertake M&As with the strategic purpose of bringing external resources under control. These resources may not be limited to those owned internally by the target firm. The limited research on externally derived network positions and resources may lead to an incomplete understanding of the acquisition phenomenon. This study intends to bridge the gap between the literature of interfirm networks and M&As.

Third, this study examines the contextual factors in which the target's network positions generate the greatest value for the acquirer. Prior M&A studies have examined the characteristics of the resources, such as the relatedness and complementarity, as an indication of the opportunity for redeploying resources and creating synergy (Finkelstein 2009; Makri, Hitt, and Lane 2010; Sears and Hoetker 2014; Yu, Umashankar, and Rao 2016). Nonetheless, these studies have a sole focus on the *internal* resources of the firm, which may not directly apply to the situations in which synergy is created from integrating network positions and resources. Saboo et al. (2017) examine how the relational overlap between the acquirer and the target affects acquisition performance. Nonetheless, the contingent value of network positions is rarely explored in the M&A literature. Essentially, gaining access to the contractual relationships of the target firm through M&As does not necessarily indicate that the acquirer can exploit these relational resources. This study explores the factors that affect the extent to which the acquirer benefits and creates synergy from the target's network positions.

This study focuses on one important network structure and position of the target firm—centrality—and examines its main and contingent effects on the shareholder value of the acquiring firm. *Centrality* refers to the extent to which the focal firm is connected to its partners (Freeman 1979). It is defined as the number of direct ties that the firm has formed in its alliance network (Wasserman and Faust 1994). Centrality captures distinctive structural traits of a firm's network position as it is related to the size of direct ties formed by a particular firm in an egocentric network. Building on the notion that interorganizational ties serve as conduits that channel resources and information between actors, we posit that centrality provides unique resource and positional benefits that may influence the value creation of M&A deals.

This study extends beyond the direct impacts of the target's network positions and explores the conditions under which the network positions of the targets can create more values for the acquirers. M&As bring two separate legal entities into one through the transfer and integration of assets and resources. The value creation of M&As is not only dependent on the acquirer's resource-picking in terms of the choice of target firms, but it also is determined by the resource deployment of the acquirers. We examine two sets of factors that influence the value creation of acquisition deals in which the targets have advantageous network positions. We consider: (1) the potential synergistic combination of network resources; and (2) the acquirer's ability to exploit such a network position for competitive advantage. More specifically, we examine the stock market's response to the combined centrality, which captures the anticipated benefits and potential synergy from the combined network resources of these parties. With regard to the acquirer's ability to exploit network positions, we examine the impacts of the relative centrality on the acquirer's shareholder value. We further examine the moderating effects of related deals and the acquirer's prior experience in the target's industry on the creation of shareholder value from the target's network position.

In this study, we construct a sample of 728 completed acquisitions in the United States between 1990 and 2011 to test our proposed hypotheses. We document that the stock market responds positively to the acquisition of a target firm that holds a central position. We also find that the combined and relative centralities of two firms are perceived positively by the stock market, leading to improved shareholder value for the acquirer. Furthermore, the positive relationship between the target's centrality and the acquirer's shareholder value is stronger when the deal relates to, or the acquirer has prior experience in, the target's industry.

Note that one important concern is the possible endogeneity issue of using network centrality measures as our independent variables. The acquirers may strategically choose their targets with certain characteristics related to their network positions. Therefore, our estimation may be biased if the selection process is not random. To address this issue, we follow existing literature (Popov and Udell 2012) and use the Heckman two-stage model (1979) to predict the likelihood of an acquirer selecting a target firm with a specific network position. We then calculate the inverse Mills ratio and use it as an additional explanatory variable. The inverse Mills ratio allows us to control for selection bias (Hamilton and Nickerson 2003). We find that our results are robust to the adoption of Heckman two-stage model (1979) to deal with the endogeneity issue.

The remainder of this paper is structured as follows. In the next section, we review the existing literature and propose our hypotheses regarding the main and contingent effects of the target's network positions on the acquirer's shareholder value creation. We then detail the data, sample, measures, and statistical methods. In the end, we present the empirical results and discuss the findings, contributions, and implications of the paper.

EXISTING THEORIES AND OUR HYPOTHESES

One focus of the M&A research is to understand the sources of gains of value creation in M&As (Hitt, Harrison, and Ireland 2001). Researchers have identified several determinants, including acquirers' corporate governance (Masulis, Wang, and Xie 2007), corporate diversification (Lamont and Polk 2001), managerial objectives (Morck, Shleifer, and Vishny 1990), top executive (Walters, Kroll, and Wright 2007), and others.

One major factor that drives value stems from the synergy created by the combination of two firms. Synergy is generated when the value of the combination of the two firms is superior to the sum of the two stand-alone values (Bradley, Desai, and Kim 1988; Jensen and Ruback 1983). Research has focused on various aspects that may affect synergistic gains, such as the attributes of the acquirer and the target, and the transaction between them. These factors include relatedness and complementarity of resources (Bauer and Matzler 2014; Finkelstein 2009; Kim and Finkelstein 2009), redeployment and sharing of resources (Capron et al. 1998; Capron and Hulland 1999; Capron and Pistre 2002), the acquirer's M&A experience and learning (Haleblian and Finkelstein 1999; Hayward 2002), and experience and information asymmetries of merging parties (Cuypers, Cuypers, and Martin 2017).

These studies have offered great insights into how M&As might create value. Nonetheless, most of the research has focused on internal resources as a source of synergistic gains. Less attention is devoted to resources beyond a firm's boundary—network positions and resources embedded in interorganizational relationships—as a potential source of value creation. Strategy literature has widely documented that a firm's network positions can be a source of competitive advantage (Gulati 1998; Gulati et al. 2000). The research of network positions, however, is limited in M&A literature. Prior M&A research that examines interorganizational relationships tends to treat interfirm ties as an information-gathering device that alleviates uncertainty of M&As (Beckman and Haunschild 2002; Reuer, Tong, and Wu 2012), overlooking the resource and positional benefits of network positions. This study provides an alternative view of network positions in M&As.

Resource and Positional Advantages of Network Positions

Social network theorists take a structural perspective in understanding the influence of interorganizational relationships. A firm's network position is the structure of interorganizational relationships through which a firm is linked to other organizations (Laumann, Galaskiewicz, and Marsden 1978). These interorganizational relationships are formed through voluntary interfirm arrangements that involve constant information exchange or resource sharing (Gulati 1998). These relationships are perceived as valuable resources that are embedded in the social structure within which an organization is located. The structures and patterns of interorganizational relationships determine the distribution of network resources among organizations, which, in turn, facilitate or constrain the action and performance of an organization (Granovetter 1985; Gulati 1998; Marsden and Friedkin 1993).

Social network theory suggests two attributes of the target firm's network positions and structures that can affect the value creation of M&A deals: resource and positional advantages. In particular, the former is based on the notion of "networks as pipes" (Podolny 2001) that channel information and resources embedded in the network. It features resource and information benefits derived from the network position occupied by the focal firm, which is termed *network resources* (Gulati 1998; Lavie 2006). The latter attribute emphasizes the ancillary benefits derived from the network position itself. Network resources include the power, status, and endorsement induced by the network position. These two attributes work in tandem as the former substantiates the latter. Consequently, they can be a source of value creation in M&As.

Centrality is defined as the sum of direct ties formed by the focal actor; the more interorganizational linkages, the more central a position the focal firm occupies. The acquisition of a central target can contribute to value creation for two reasons.

1. A central position provides the target firm with a resource advantage that is unmatched by other firms. As interorganizational relationships are an important way to gain resources located beyond a firm's boundary (Gulati and Singh 1998), the extensive linkages of a highly central firm enable access to valuable information and resources embedded in the network. The resource advantages include access to unique knowledge and technologies (Mowery, Oxley, and Silverman 1996; Powell, Koput, and Smith-Doerr 1996), complementary capabilities and resources (Gulati 1999; Stuart 2000), innovative capabilities and expertise (Powell, Koput, and Smith-Doerr 1996; Shan, Walker, and Kogut 1994), and opportunities for new markets (Jensen 2003). It is widely documented that a central position enhances a firm's innovation (Powell 1998; Rothaermel and Deeds 2004; Stuart 2000), performance, and growth potential (Gulati 1998; Lavie 2006; Powell 1998; Powell, Koput, and Smith-Doerr 1996; Shan, Walker, and Kogut 1994; Tsai 2001).
2. A central network position serves as a signal to major stakeholders about the quality of the target firm. One major challenge for the acquirer is the complexity and uncertainty associated with the selection and valuation of the target firm. As M&As are a means to obtain needed resources possessed by the target firm, the quality of the target firms' assets, resources, and capabilities can affect the extent to which value is created through M&As. Nonetheless, the selection process is complicated by information asymmetry (Stiglitz 2002) in that the acquiring firm has incomplete infor-

mation about the seller's true value. The information asymmetry may result in *ex-ante* market failure in which the target firm is inaccurately valued, worthwhile acquisitions are not pursued, and an efficient M&A transaction is not feasible (Akerlof 1970; Balakrishnan and Koza 1993).

In M&A transactions where the underlying quality differences of the potential target are not transparent, interorganizational associations and affiliations provide information cues regarding the target firm's intrinsic value and can be used to differentiate a specific set of targets. Network ties serve as observable "gestures of approval" (Gould 2002, 1147) of the focal firm's resources and capabilities. The target firm's large number of linkages implies that the firm's resources and capabilities are valuable to and in demand by various partners (Ozmel, Reuer, and Gulati 2013). Such a position also certifies the firm's experience, competencies, and trustworthiness as a reputable exchange partner (Gulati and Higgins 2003; Pollock and Gulati 2007; Sorenson and Stuart 2001; Stuart, Hoang, and Hybels 1999). The endorsement derived from interorganizational associations enhances the legitimacy of the firm and positively influences its survival, growth, and performance (Baum, Calabrese, and Silverman 2000; Podolny 2010; Sauder, Lynn, and Podolny 2012; Stuart 2000; Stuart, Hoang, and Hybels 1999). Hence, a target firm's central position manifests the firm's unobservable quality and facilitates economic transactions that may otherwise fall through because of information asymmetry (Benjamin and Podolny 1999). It increases buyer or investor confidence regarding the claims of the target's resources and capabilities, and the future prospect of M&A deals (Qi et al. 2013; Ragozzino and Reuer 2007; Reuer, Tong, and Wu 2012).

Taken together, the resource and positional advantages of a central target firm can be a source of value creation in M&A deals. Such a network position certifies the target firm's quality, which can positively influence the stock market's valuation of M&A deals.

Hypothesis 1: *The centrality of the target firm in alliance networks is positively associated with the acquirer's shareholder value creation.*

Synergistic Network

So far, we have mainly focused on the target's network positions as a source of value creation in M&As. Nonetheless, M&As' value can be created from the synergy of the combined network resources. We examine how the stock market responds to combined centrality, which is defined as the centrality of the acquirer after combining the target firm's contractual relationships into its preexisting alliance portfolio. The combined centrality does *not* measure the actual centrality of the acquirer after acquisition; it denotes the anticipated synergy and future prospect of the combined network resources after acquisitions.

Prior M&A literature mainly focuses on internal resources as the primary motive for acquisitions. Nonetheless, firms may undertake M&As with the strategic purpose of achieving network synergy, i.e., an acquirer's network position is favorably improved from the acquisition (Hernandez and Shaver 2017). In particular, an acquirer may select the target based on how well the target's network ties alter the acquirer's existing network position. This network synergy can drive the acquirer's choice of target firm (Hernandez and Shaver 2019).

Following the same logic, we argue that the stock market responds positively to the potential synergy of combined network resources, i.e., combined centrality. Through obtaining access to and inheriting the target firm's network ties, the acquirer attains a more advantageous network position. The addition of network ties through the acquisition allows the acquirer to overcome its limited ability to form ties, to access desirable partners of the target firm, or to preempt its competition from forming critical contractual relationships (Hernandez and Shaver 2017). Using a simulation that modeled the evolution of network structure through acquisitions, Hernandez and Menon (2017) illustrate that acquisitions can improve the acquirer's network position, reshape network structure in the acquirer's favor, and consequently enhance the acquirer's performance. Therefore, after combining network resources, the acquirer gains improved centrality, tends to be noted more often, and may receive more opportunities for gaining resources (Gulati 1995, 1995; Gulati and Gargiulo 1999). Its prominent position also allows the acquirer to exert influence or control over how the firm is perceived by other stakeholders (Martin 2009).

Hypothesis 2: *The combined centrality of the acquirer and the target firm is positively associated with the acquirer's shareholder value creation.*

Acquirer's Ability to Exploit the Target Firm's Network Positions

The acquisition of a well-positioned target firm, however, does not mean that the acquirer could maximize the benefits from the target's advantageous network position unless it is equipped with the necessary ability to manage and utilize these network positions. Several factors may influence the extent to which the acquirer could create value from the target firm's central position. They include relative centrality, related deals, and the acquirer's prior experience in the target's industry, which will be discussed in detail.

Relative centrality is defined as the relative difference in centrality between the acquirer and the target. It denotes the asymmetry in their network positions and alliance experiences. That is, a high relative centrality indicates the acquirer's advantageous network positions and experience in managing alliances. We argue that the relative centrality of the acquirer to the target contributes to shareholder value creation for three reasons. First, even if the acquirer gains access to the target's interfirm relationships through M&As, the acquirer's lack of alliance experience may cause disturbance and inefficiency in managing numerous contractual relationships all at once. Thus, the benefits of acquiring a central target could only be realized when the acquirer has the capabilities to manage multiple alliances. When the acquirer has taken part in multiple alliances, the acquirer learns to manage alliances and develop alliance management capabilities over time (Anand and Khanna 2000). This accumulated alliance experience allows the acquirer to effectively manage the target's contractual relationships after the acquirer inherits these network ties from the target. Second, relative centrality reflects the power of asymmetry between the acquirer and the target that can be leveraged in the acquirer's favor. The acquirer's relatively stronger bargaining power allows the acquirer to extract more gains (Aktas, De Bodt, and Roll 2010), minimize power struggles between the acquirer and the target, and facilitate effective integration of network resources (Gnyawali and Madhavan 2001; Yang et al. 2011). Furthermore, the acquirer could utilize its extensive networks for information gathering that may result in a more accurate valuation of the target firm, lowering overpayment risks (Ahuja et al. 2009). Third, relative centrality could translate into the status differential between the acquirer and the target, which is compatible with their expected roles in M&A transactions. Specifically, when the acquirer takes a leadership role aligned with its status, M&A transactions could be conducted smoothly (Podolny 1993; Podolny 2001; Shen et al. 2014). Otherwise, the misalignment between the two parties' status and roles may cause ambiguity, confusion, and conflicts that hinder the success of the transaction.

Hypothesis 3: *The relative centrality of the acquirer to the target firm is positively associated with the acquirer's shareholder value creation.*

The relatedness of M&A deals can affect the acquirer's ability to exploit resource opportunities from the target's central position. The M&A deals are related when the acquirer and the target operate in the same primary industry. We argue that related deals increase the acquirer's shareholder value from the acquisition of a central target for two reasons. First, when the acquirer and the target operate in the same industry, the acquirer is readily equipped with the knowledge and capabilities to integrate and deploy the target's network resources (King et al. 2004). The familiarity with the industry enables the acquirer to effectively manage the target's contractual relationships and capitalize on these network resources (Capron, Dussauge, and Mitchell 1998; Cloodt, Hagedoorn, and Van Kranenburg 2006; Grimpe and Hussinger 2014; Hagedoorn and Duysters 2002; Makri, Hitt, and Lane 2010). Second, related deals accentuate market consolidation and increase the acquirer's bargaining power over its contracting partners, suppliers, or buyers. The acquirer could increase its power and extract higher economic rents from the contractual relationships. Related deals also provide opportunities for consolidating contractual relationships and redeploying network resources (Haleblian et al. 2009). Therefore, we propose the following hypothesis.

Hypothesis 4: *Related deals positively moderate the relationship between the centrality of the target firm and the acquirer's shareholder value creation. Specifically, when the acquiring firm and the target firm operate in related industries, the relationship is stronger.*

The acquirer's prior experience in the target's industry can influence the extent to which the acquirer creates value from the target's central position. M&A literature has treated firms as learning actors and documented that learning is an important means to resolve uncertainties inherent in M&As. In particular, organizational learning is a dynamic process in which the firm engages in activities repeatedly, draws inferences from past experience, and stores the inferred knowledge for future use (Levitt and March 1988).

An acquirer's prior industry experience is defined as its M&A and alliance activities conducted in the target industry prior to the focal acquisition. Such a definition reflects the fact that alliances and acquisitions are not independent events and can be the sources of learning in the context of acquisitions (Lin et al. 2009; Yang et al. 2011). As firms carry out multiple acquisitions in the target's industry, they learn from repeated activities and accumulate experience. They also develop expertise about the acquisition process and gain knowledge about the target's industry. Their acquisition experience could enhance their ability to manage the acquisition process and integrate the target firm's resources smoothly (Haleblian and Finkelstein 1999; Hayward 2002). Alliance activities in the target's industry also provide another avenue for learning. Recent studies have shown that experience accumulated from alliances drives acquisition behaviors (Lin et al. 2009). Firms can learn from their partners and develop crucial capabilities and expertise that can be re-deployed in the future (Khanna et al. 1998). The flexibility of alliances allows the firm to experiment with novel technologies or new opportunities (Mody 1993). In this regard, firms can learn from the alliance experience and apply it in the pursuit of acquisitions (Porrini 2004).

Prior target-related industry experience is crucial for the acquirer to capture value from the acquisition. This prior knowledge enables the acquirer to recognize the value of the target's network resources and mobilize the needed resources embedded in a network. These network resources, such as the trust of customers and suppliers, implicit knowledge, and capabilities of alliance partners, are best transferred and utilized by experienced acquirers. Thus, the acquirer's prior experience increases the value derived from a central target.

Hypothesis 5: *The acquiring firm's prior experience in the target firm's industry positively moderates the relationship between the centrality of the target firm and the acquirer's shareholder value creation. Specifically, when the acquirer has more prior experience in the target firm's industry, the relationship is stronger.*

METHOD

Data and Sample

To investigate whether and to what extent the stock market values the target firm's alliance network position in a particular acquisition deal, we first extract data from the Thomson Financial SDC Platinum (SDC) Mergers and Acquisitions Database and retrieve acquisition deals between January 1, 1995 and December 31, 2011. To construct our sample, we focus on U.S. targets acquired by publicly traded U.S. companies. We require our sample acquisitions to have "complete" deal status, "friendly" deal attitude, and more than $1 million in transaction value as recorded in the SDC database. Following convention (Graham, Lemmon, and Wolf 2002, Masulis, Wang, and Xi 2007), we exclude those deals in which the acquirers are financial firms (SIC codes 6000–7000) and utility companies (SIC codes 4900–4999) due to their highly regulated environments. In addition, we require that an acquiring firm not own any shares in the target firm and purchase at least 51 percent of the target firm's outstanding shares in a particular acquisition deal. To be included in our sample, the acquiring firms should have sufficient stock price information from the University of Chicago's Center for Research in Security Prices (CRSP) Daily Stock Price and Returns file, and sufficient financial information from the Compustat database.

We retrieve alliance activities from SDC Strategic Alliance/Joint Venture database during the period from 1990 to 2011. The SDC Alliance Database has been documented as quite accurate and comprehensive in its coverage of U.S. interfirm collaborations (Schilling 2009). We include various kinds of collaborative activities (e.g., research and development agreements, manufacturing agreements, marketing agreements, and supplier agreements) used in the construction of interfirm networks. As the actual dates of alliance termination are often unreported, we adopt a five-year window to construct interfirm networks (Lavie 2007; Schilling and Phelps 2007; Stuart 2000). We aggregate alliances from year $t - 4$ to year t to construct a particular firm's network centrality in year t. We build undirected binary adjacency matrices for each interfirm network (Wasserman and Faust 1994). We code 1 in the corresponding adjacency matrix when two firms are in a collaborative relationship and 0 otherwise.

We supplement the acquisition sample with the stock price data, financial indicators, and the measures of alliance network positions for both the acquiring firms and the target firms. Our sampling procedure yields a sample of 728 acquisition deals involving 481 unique acquiring firms in 166 unique 4-digit SIC industry segments. Out of the 728 acquisition deals, 370 involve public targets, 280 involve private targets, and 78 involve subsidiary targets. The target firms operate in 187 4-digit SIC industries, with 51% in high-tech industries as defined by Loughran and Ritter (2004).

Measures

Dependent Variable

The event study method is used to estimate the stock market's evaluation of the changes in a firm's value following the announcement of an M&A deal. We first design the announcement date as $t = 0$ in event time, and estimate a market model of each firm's stock returns using a single-index market model (Brown and Warner 1985; Moeller, Schlingemann, and Stulz 2005) based on the CRSP equal-weighted return index,

$$R_{it} = \alpha_{it} + \beta_i R_{mt} + \varepsilon_{it} \tag{1}$$

where

R_{it}	is the return for security i on day t
R_{mt}	is the return on a market index on day t
α and β	are market model coefficients

For each firm i, we estimated the market model coefficients using daily returns for the 255-day period $t = (-300, -46)$.

We then used the estimated coefficients (α and ß) from this model to predict daily returns for each firm i over the "event window"—i.e., in the days immediately surrounding the acquisition announcement. Abnormal returns (ARs) for each firm on each day of the event window are the deviations of the actual return from the expected return for security i on date t, given by the market model. They are computed as:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}) \tag{2}$$

where

AR_{it} is the abnormal return for firm i on day t

The cumulative abnormal returns (CARs) for each firm i are calculated by summing the ARs over the event window. As suggested by Corhay and Rad (1996), we control for conditional variance in event-study regression models for more efficient and robust estimation. We also employ the GARCH (1, 1) model to allow for conditional heteroscedasticity in the errors (Karniouchina, Uslay, and Erenburg 2011). Following Mikkelson and Partch (1985), we calculate cumulative abnormal returns (CARs) for the one-day (0, 0), three-day (–1, 1), and seven-day (–3, +3) event windows, where day 0 is the acquisition announcement date (Moeller, Schlingemann, and Stulz 2005).

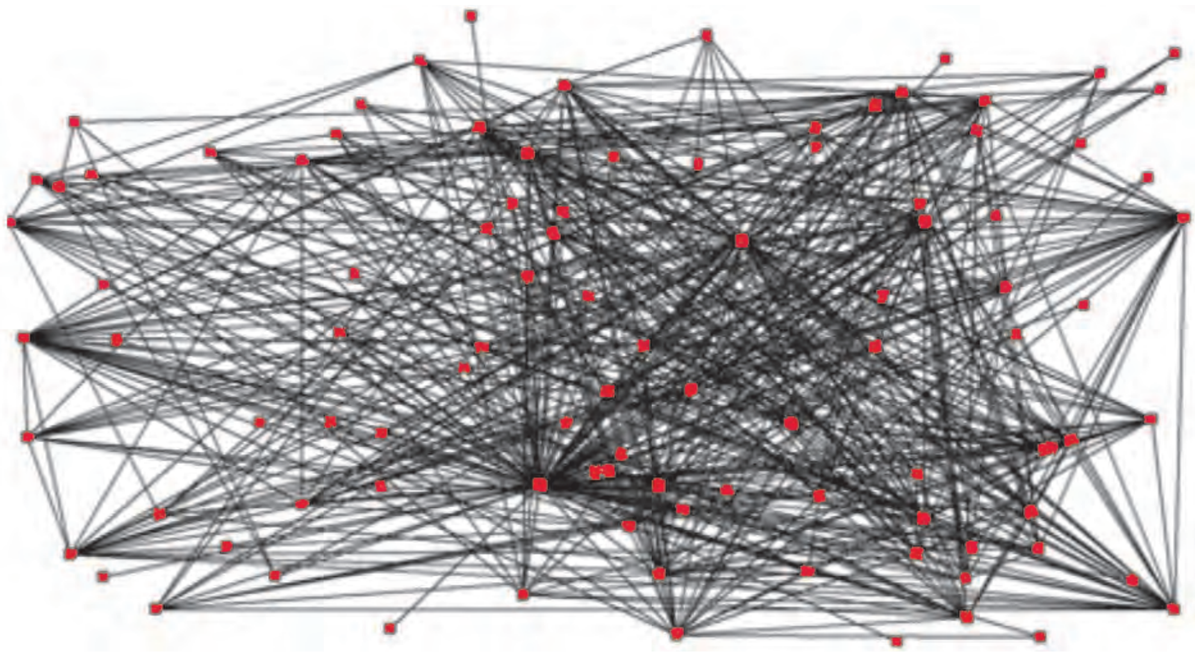
Independent Variables

Centrality. In this study, we focus on the centrality of the target firm in the alliance networks. Among several measurements of centrality (Freeman 1979), we believe degree centrality is the most appropriate indicator for this study. The major reason is that the simplicity of degree centrality could capture the visibility of such a network position. Other centrality measures, such as betweenness centrality or eigenvector centrality (Bonacich 1987), require substantial calculations and sophisticated interpretations, which reduce their viability as a market signal. We measure centrality by the total number of alliance partners that a target firm has established during the five-year window preceding the focal M&A deal. Given that partner firms may be involved in multiple alliances, we further adjust our measure of centrality by incorporating the tie weights in the calculation (Barrat et al. 2004; Opsahl, Agneessens, and Skvoretz 2010) based on the strength of relationships. This measure accounts for the strengths of the ties and more accurately reflects the resources embedded in the network.

Relative centrality. We generate a set of centrality-related measures to capture the interaction between the acquirer's and the target's network positions. We measure relative centrality as the ratio of the acquirer's centrality to the target's centrality (Yang, Lin, and Peng 2011). We follow the aforementioned approach to calculate the acquirer's centrality to generate the measure of relative centrality. The higher this value, the more asymmetry in the network positions of acquirer and target.

Combined centrality. We measure the combined centrality as the sum of the centrality of the acquirer and the target in an M&A deal. We do not calculate the acquirer's actual centrality after the alliance ties between two firms are integrated, as our purpose is *not* to examine the actual network synergy. We reason that the combined centrality presents as a high-level market signal and denotes the stock market expectation on the potential network. In Figure 1, we provide a visualization of the social network using our sample data.

FIGURE 1. Visualization of Social Networks



Moderating Variables

Related deal. As relatedness between the acquirer and the target increases value creation of acquisitions (King, Slotegraaf, and Kesner 2008; Puranam and Srikanth 2007), we include a dummy variable, *related deal,* to measure whether the target and acquirer operated in the same primary industry. Specifically, we adopt Fama-French 49 industry coding system to classify the industry segments of our sample acquirers and targets (Masulis, Wang, and Xie 2007; Li and Chi 2013; Shi, Yan, and Robert 2017). The variable is coded as 1 if the target and the acquirer are in the same Fama-French 49 industry,[1] and 0 otherwise.

Acquiring firm's prior experience. To construct a measure capturing the acquiring firm's prior experience in the target firm's industry, we focus on both alliance and acquisition experience. We reason that organizational learning can occur through both alliance activities and acquisition events. We collect detailed information about alliance and acquisition activities of our sample acquiring firms in the target firms' respective industries. We use the count variable by summing the total number of identified alliance and acquisition events during the 5-year window preceding the focal acquisition deals and take the natural logarithm of this measure to normalize its distribution.

Control Variables

We include a set of variables to account for the variances of acquirers, targets, and deals. Note that all control variables are measured at year $t - 1$. Specifically, we include *acquirer's centrality* as a control, as it may affect the network synergy generated from the acquisitions (Hernandez and Menon 2017). We measure the *size of acquiring firms* as the natural logarithm of book assets. As reported by Moeller,

[1]Professor Kenneth French generously provides the data, which are available here: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Schlingemann, and Stulz (2004), larger acquirers consistently experience lower abnormal returns upon the announcement of the deal. We include the *acquirer's Tobin's q* as a control because high Tobin's q firms (glamour firms) are more likely to experience poor post-acquisition performance (Rau and Vermaelen 1998). It is measured as the book value of assets minus the book value of equity plus the market value of equity, divided by the book value of total assets. We also include *acquirer's book leverage* as an additional control, which is measured as the ratio of long-term debt to the book value of assets. We calculate the *acquirer's ROA* as the ratio of net income over book value of assets to control for its performance.

We enter variables capturing various characteristics of the target firms which may affect the stock market's valuation of the M&A deals. We include the size of the target firm (*target size*) measured as the natural logarithm of its book assets. We also include *relative size* to account for the size effect (Agrawal, Jaffe, and Mandelker 1992). It is calculated as the ratio of acquirer size to the target size. We account for the variance of the target firm's performance in the model. Given the limited data availability of the private targets, we calculate the ratio of net income over firm total sales to capture the targets' profitability *(target performance)*. We also include a *public target* dummy if a target is an exchange-listed firm. Following Loungran and Ritter (2004), we use a dummy variable, *high-tech target,* to capture the firm-specific uncertainty and hard-to-value assets of the target firm.

We include a set of indicators to capture various deal characteristics. The acquisition's medium of exchange contains important information (Carleton et al. 1983; Eckbo, Giammarino, and Heinkel 1990). We, therefore, include the *all-cash payment* dummy, which refers to deals purely paid with cash. We include *competing bids* dummy, which equals 1 if the target receives more than one bid in a particular M&A deal. *Tender offer* dummy is also included to control for its impacts on the acquirer's abnormal return. It equals 1 if the M&A deal is a tender offer.

We examine the effects of the complementarity between acquiring and target firms on acquirers' shareholder value creation. We use two input/output (IO)–based measures, input and output complementarity, to measure the complementarity between acquiring and target firms. Following the approach of Fan and Lang (2000) and Fan and Goyal (2006), we measure industry complementarity based on the "Use Table" of "Benchmark Input-Output Account for the U.S. Economy" from the U.S. Bureau of Economic Analysis (BEA). The "Use Table" is a matrix of the dollar value of goods flowing between pairs of roughly 500 IO industries. Industry complementarity captures how many input and output markets are shared by two industries. A large coefficient of *input complementarity* means that two industries have a large overlap in goods purchased from upstream industries. Likewise, a large coefficient of *output complementarity* means that the two industries have a large overlap in goods provided for downstream industries.

We include industry-fixed effects for the targets to control for the difference in industries in terms of M&A activities. We also include year fixed effects to control for economy-wide shocks and timely trends.

Statistical Methods

We conduct a standard event study to estimate the acquirer's abnormal returns upon the announcement of M&A deals. The detailed procedures are described earlier in "Dependent Variable." We use ordinary least squares (OLS) regression to estimate the main effect of the target's centrality and its contingent effects on the acquirer's cumulative abnormal returns. As acquiring firms may participate in acquisition activities repeatedly, we use clustered standard errors by acquiring firms to account for residual dependence across acquisition deals by the same acquirer (Petersen 2009). We mean-center the continuous variables (e.g., centrality and acquirer's prior experience) before they are entered into the interaction terms.

An important concern of our study is the endogeneity issue that arises when the acquiring firms strategically choose their targets with certain network centrality characteristics. To address this issue, we follow existing literature (Popov and Udell 2012) and use the Heckman two-stage model (1979) to predict the likelihood of an acquirer selecting a target firm with a specific network position. The Heckman model incorporates information regarding groups of firms that make different strategic choices, thus allowing us to *correct the bias caused by the selection problem*. Specifically, we estimate a probit model of the choice of a centrally located target (i.e., a target centrality score above the median) as a function of an acquirer's centrality, acquirer's prior M&A experience, acquirer size, target size, target's asset intangibility, target book leverage, target's public status, and a target's operating in the high-tech industry. The estimated probit model has a log-likelihood of –210 and a McFadden's Pseudo R-squared of 8.44 percent. Following Veall and Zimmermann (1996), we compare the prediction accuracy of our model (0.67) with a blind guess (0.50) by calculating $\lambda' = (0.67 - 0.50)/(1 - 0.50) = 0.35$, which reveals a significant 35 percent improvement over a blind guess (Hoetker 2007). These statistics indicate the appropriateness of the choice of independent variables and the overall fit of the probit model. We calculate the inverse Mills ratio based on the probit model, which is subsequently entered into all regression models as an additional control variable (Heckman 1979). The inverse Mills ratio not only allows us to control for selection bias but also signifies the direction of such selection (Hamilton and Nickerson 2003). Nonetheless, in our regression analysis, the inverse Mills ratio bears an insignificant coefficient, which indicates that our results are not particularly driven by the aforementioned endogeneity concern.

RESULTS

Table 1 reports summary statistics and correlations of variables used in our regression analysis. We also cautiously check the correlations among variables and calculate the variance inflation factors to ensure multicollinearity is not a concern.

Table 2 presents the regression results of the effects of the target firm's centrality on the acquirer's abnormal return at the time of the acquisition announcement. In Model 1, we report the baseline regression result that includes all control variables. In Model 2, we model the stock market's abnormal return as a function of the target's centrality, along with a set of control variables. We document a statistically significant and positive coefficient of the target's centrality. Our result reveals that, all else being equal, stock markets value targets' central network position positively. We include the acquirer's network centrality as an additional control. However, adding this control does not take away the significance of our variable of interest, the target's centrality. Using the result in Model 2, we can further gauge the economic significance of the target's centrality. Specifically, a

TABLE 1. Summary Statistics and Correlation Matrix

	Mean	Std	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. CAR (−1, 1)	−0.005	0.10	1.00																				
2. Target's centrality	2.00	0.38	0.07	1.00																			
3. Acquirer's centrality	2.76	1.78	0.06	0.01	1.00																		
4. Relative centrality	1.44	0.98	0.05	**−0.30**	**0.93**	1.00																	
5. Combined centrality	4.76	1.83	0.08	**0.21**	**0.98**	**0.84**	1.00																
6. Acquirer Tobin's q	3.64	9.28	−0.09	−0.03	0.02	0.02	0.01	1.00															
7. Acquirer ROA	0.01	0.26	0.03	0.06	**0.09**	0.07	**0.10**	**−0.08**	1.00														
8. Acquirer leverage	0.20	0.19	−0.02	−0.05	−0.07	−0.05	**−0.08**	**−0.11**	−0.03	1.00													
9. Acquirer's prior experience	0.50	0.64	**0.19**	−0.02	**0.12**	**0.11**	**0.11**	−0.03	−0.02	−0.01	1.00												
10. Acquirer size	21.16	2.32	−0.07	0.01	**0.45**	**0.41**	**0.44**	**−0.15**	**0.23**	**0.11**	**0.11**	1.00											
11. Relative size	0.91	0.12	0.06	**−0.08**	**−0.28**	**−0.24**	**−0.29**	0.03	**−0.08**	−0.01	0.01	**−0.48**	1.00										
12. Target size	19.08	2.39	−0.02	−0.07	0.08	0.09	0.06	**−0.10**	0.12	0.10	0.10	**0.37**	**0.62**	1.00									
13. Target performance	0.05	3.38	0.00	0.02	−0.02	−0.02	−0.01	−0.02	0.01	0.04	0.04	**0.08**	−0.02	0.03	1.00								
14. Public target dummy	0.51	0.50	**−0.18**	−0.06	−0.07	−0.04	**−0.08**	0.01	0.02	0.04	0.21	**0.15**	0.06	**0.22**	0.01	1.00							
15. High-tech target dummy	0.51	0.50	**−0.08**	**0.11**	**0.27**	**0.22**	**0.29**	0.08	−0.04	**−0.27**	0.06	−0.04	**−0.10**	**−0.15**	**−0.08**	**−0.10**	1.00						
16. Related deal	0.57	0.50	−0.07	0.01	**−0.17**	**−0.15**	**−0.16**	−0.02	−0.07	0.02	0.07	**−0.13**	**0.10**	0.02	−0.02	**0.18**	**−0.11**	1.00					
17. Input complementarity	0.51	0.37	−0.13	0.02	−0.03	−0.04	−0.02	0.03	**−0.13**	−0.02	0.02	**−0.11**	0.06	−0.03	0.00	0.05	0.06	**0.22**	1.00				
18. Output complementarity	0.55	0.34	−0.13	0.05	0.03	0.00	0.03	0.08	**−0.13**	−0.03	0.08	**−0.09**	0.01	−0.06	0.03	**0.08**	**0.12**	**0.19**	**0.47**	1.00			
19. All cash payment dummy	0.21	0.41	0.07	0.05	**0.13**	**0.12**	**0.14**	−0.07	0.07	−0.07	0.10	**0.14**	**−0.21**	**−0.11**	0.04	**0.08**	**0.13**	**−0.09**	−0.05	−0.03	1.00		
20. Competing bids	0.39	0.49	0.07	0.06	0.00	−0.01	0.02	0.01	0.01	−0.02	−0.02	0.02	−0.02	−0.00	0.02	−0.06	0.03	0.02	0.01	0.03	0.00	1.00	
21. Tender offer	0.23	0.42	0.04	−0.05	0.01	0.04	0.00	−0.02	0.05	−0.03	−0.02	0.02	0.05	0.07	−0.06	0.03	0.01	0.02	−0.06	−0.02	0.06	0.01	1.00

Note: N = 728, and those numbers in **bold** are significant at 5% level.

TABLE 2. Effects of the Target's Network Positions on the Acquirer's Abnormal Returns

Independent Variables	Dependent Variable CAR (−1, 1)			
	Model 1	Model 2	Model 3	Model 4
Target's centrality		0.021**		
		(0.008)		
Combined centrality			0.063**	
			(0.029)	
Relative centrality				0.014+
				(0.009)
Acquirer's centrality		0.011**		
		(0.006)		
Related deal	−0.001	0.000	0.000	0.000
	(0.008)	(0.007)	(0.008)	(0.007)
High-tech target	−0.022**	−0.023**	−0.022**	−0.022*
	(0.011)	(0.011)	(0.011)	(0.011)
Public target	−0.022*	−0.019*	−0.020*	−0.019*
	(0.011)	(0.011)	(0.011)	(0.011)
Input complementarity	−0.019	−0.021*	−0.021*	−0.021*
	(0.012)	(0.012)	(0.012)	(0.012)
Output complementarity	−0.014	−0.017*	−0.016*	−0.015
	(0.009)	(0.009)	(0.009)	(0.009)
Acquirer's Tobin's q	−0.000	−0.000	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Acquirer's leverage	−0.023	−0.023	−0.017	−0.023
	(0.024)	(0.024)	(0.023)	(0.024)
Acquirer's ROA	−0.005	−0.005	−0.004	−0.002
	(0.015)	(0.014)	(0.014)	(0.015)
Acquirer size	0.046*	0.037*	0.039*	0.040*
	(0.025)	(0.021)	(0.022)	(0.022)
Target size	−0.054*	−0.049*	−0.051*	−0.051*
	(0.029)	(0.026)	(0.027)	(0.027)
Relative size	1.147*	1.034*	1.083*	1.069*
	(0.635)	(0.565)	(0.592)	(0.580)
Target's performance	−0.001	−0.000	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
All cash payment dummy	0.021***	0.019**	0.020**	0.020**
	(0.008)	(0.008)	(0.008)	(0.008)
Competing bids	0.015	0.015	0.015	0.016
	(0.010)	(0.010)	(0.010)	(0.010)
Tender offer	0.011	0.011	0.010	0.009
	(0.012)	(0.011)	(0.011)	(0.011)
Inverse Mill's ratio	−0.003	−0.003	−0.003	−0.005
	(0.014)	(0.014)	(0.014)	(0.014)
Constant	−0.993*	−0.813*	−0.943*	−0.877*
	(0.561)	(0.475)	(0.526)	(0.492)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.089	0.113	0.109	0.099
No. of observation	728	728	728	728

*p < 0.1; **p < 0.05; ***p < 0.01

one-standard-deviation increase in the target's network centrality leads to 0.76 percent increase in the acquirer's CAR, which is economically significant. Thus, our empirical analyses lend strong support for Hypothesis 1.

In Model 3, we test the impacts of the combined centrality of both the acquirer and the target on the acquiring firm's abnormal returns (Hypothesis 2). Our analysis shows a significant and positive coefficient of the combined centrality, which supports Hypothesis 2. In Model 4, we examine the relative centrality of the acquirer to the target and its effects on the stock market's abnormal return upon the announcement of M&A deals (Hypothesis 3). We document a positive and marginally significant coefficient of the relative centrality. Therefore, our results reveal that the stock market does incorporate information on the relative network positions of both the acquirer and the target to assess the potential synergistic gains.

In addition, it is plausible that our centrality measures may be correlated with other firm characteristics. For example, larger firms and firms with longer track records may have more interactions with other firms, and thereby position themselves in the center for the network (Yu 2008). Following Fang et al. (2012), we adopt a two-stage approach to address this issue. In the first stage, we regress our measures of centrality on firm size and firm age. We then take the residuals from the first-stage regression as alternative measures of network centrality. In the second-stage regression, we use the residual measures of network centrality as our independent variables with the assumption that the residual measures represent the portion of network centrality measures that cannot be explained by the firm size and firm age. We find qualitatively similar results based on residual measures of centrality. For the sake of brevity, we do not tabulate and report the results of this robustness check.

In Table 3, we take a contingency approach to explore the moderating effect of deal characteristics on the value created by the target's centrality. To test Hypothesis 4, we investigate the moderating effects of related deals on the stock market performance at the announcement of M&A deals. In Model 1, we include *related deal dummy* and its interaction term with the target's centrality. We find that the coefficient of the interaction term is positive and statistically significant. The results suggest that the effect of the target's centrality on the acquirer's shareholder value creation is stronger in related acquisitions. In other words, stock markets place a higher value on the target's centrality when the acquirer enters familiar territory related to its core business. Thus, Hypothesis 4 is supported. The plot in Figure 2 illustrates the contention that related deals positively moderate the relationship between the target's centrality and the acquirer's abnormal return.

In Model 3, we examine whether the acquirer's prior experience in the target's industry allows the acquirer to increase the shareholder value from the acquisition of a centrally positioned target. We enter the interaction between the acquirer's prior experience and the target's centrality into the model. We find a positive and significant coefficient for the interaction term, which suggests that the target's centrality is more valuable if an acquirer has prior experience in the target's industry. Hence, our Hypothesis 5 is supported. The positive effect of the interaction between the target's centrality and the acquirer's prior industry experience on the acquirer's abnormal returns is presented in Figure 3.

TABLE 3. Contingent Effects of Acquirer and Deal Characteristics on the Acquirer's Abnormal Returns

Independent Variables	Dependent Variable: CAR (–1,1)		
	Model 1	Model 2	Model 3
Target's centrality	0.042***	0.022***	0.019**
	(0.012)	(0.008)	(0.008)
Target's centrality × Related deal	0.046***		
	(0.016)		
Knowledge distance		0.001	
		(0.002)	
Target's centrality × Knowledge distance		–0.006**	
		(0.002)	
Acquirer's prior experience			0.010***
			(0.004)
Target's centrality × Acquirer's prior experience			0.016*
			(0.007)
Acquirer's centrality	0.012**	0.011**	0.011**
	(0.006)	(0.006)	(0.005)
High-tech target	–0.022**	–0.022**	–0.025**
	(0.011)	(0.011)	(0.011)
Public target	–0.020**	–0.020**	–0.021**
	(0.011)	(0.011)	(0.011)
Related deal	0.000	0.008	–0.003
	(0.007)	(0.012)	(0.007)
Input complementarity	–0.021*	–0.021*	–0.018
	(0.012)	(0.012)	(0.012)
Output complementarity	–0.016**	–0.015	–0.020**
	(0.009)	(0.009)	(0.009)
Acquirer's Tobin's q	–0.000	–0.000	–0.000
	(0.001)	(0.001)	(0.001)
Acquirer's leverage	–0.024	–0.023	–0.019
	(0.023)	(0.024)	(0.023)
Acquirer's ROA	–0.007	–0.008	–0.006
	(0.014)	(0.014)	(0.014)
Acquirer size	0.036*	0.036*	0.033*
	(0.021)	(0.021)	(0.020)
Target size	–0.048*	–0.048*	–0.047*
	(0.026)	(0.026)	(0.025)
Relative size	1.011*	1.069*	0.974*
	(0.560)	(0.560)	(0.532)
Target's performance	–0.000	–0.000	–0.001
	(0.001)	(0.001)	(0.001)
All cash payment dummy	0.019**	0.018**	0.015*
	(0.008)	(0.008)	(0.008)
Competing bids	0.015	0.014	0.013
	(0.010)	(0.010)	(0.010)
Tender offer	0.010	0.011	0.011
	(0.011)	(0.011)	(0.011)
Inverse Mill's Ratio	–0.001	–0.002	–0.008
	(0.014)	(0.014)	(0.013)
Constant	–0.800*	–0.796*	–0.729*
	(0.471)	(0.471)	(0.439)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adjusted R-squared	0.120	0.118	0.154
No. of observation	728	728	728

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

FIGURE 2. Moderating Effect of Related Deals on the Relationship between the Target's Centrality and the Acquirer's Abnormal Returns

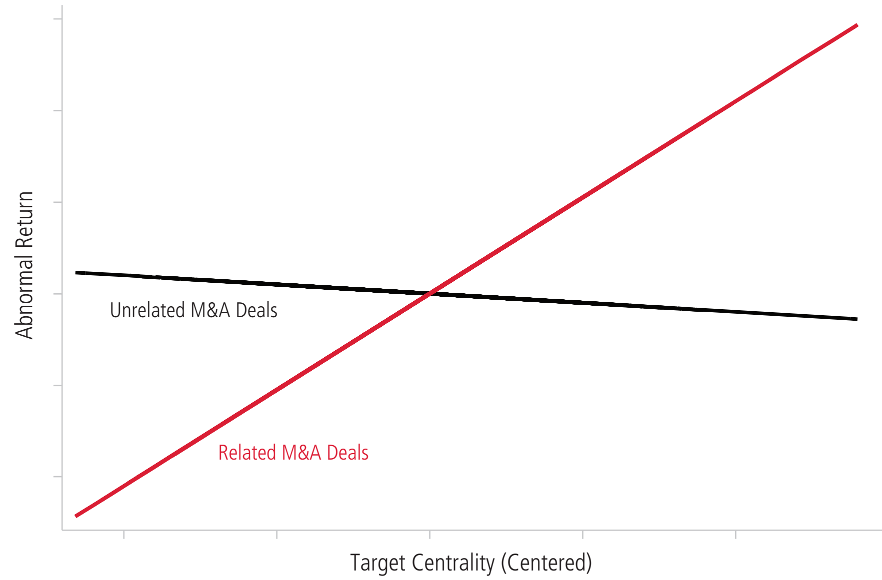


FIGURE 3. Moderating Effect of Acquirer's Prior Experience in the Target's Industry on the Relationship between the Target's Centrality and the Acquirer's Abnormal Return

Robustness Tests

We conduct several additional analyses to ensure the robustness of our results. First, we estimate the model using CAR in the seven-day event window as an alternative dependent variable. The results are qualitatively and directionally similar to the ones reported here. Second, we use an alternative measure, *knowledge distance*, to capture the dissimilarity of the industries in which the acquirer and the target operate. It is measured by the absolute value of the difference between the two firms' four-digit SIC codes. The value is then log-transformed.

In Model 2 (Table 3), the coefficient of *knowledge distance* is negative and statistically significant, which is consistent with Hypothesis 5. We further explore the possibility of the nonlinear moderating effect of *knowledge distance* to see if its influence is non-monotonic. We include quadratic terms of *knowledge distance* in our model, but do not find any nonlinear effects. Overall, our additional analyses show that the results are quite robust.

DISCUSSION AND CONCLUSIONS

Building upon the social network theory, this study examines the main and contingent effects of a target firm's network positions on the acquirer's shareholder value creation. In general, we document that the stock market responds positively to the target firm's centrality. Consistent with existing literature, our analyses reveal the beneficial effects of centrality in the context of M&As. Taking our main finding one step further, we examine the potential network synergy deriving from the combined network resources. We find that the stock market responds positively to the combined centrality of two merging firms. Consistent with the simulation results from Hernandez and Menon (2017), the results show that the acquirer's shareholder value creation is not solely determined by the network position on the target's side but also by the potential network synergy of the combined firms.

Despite the potential benefits of a target's superior network positions, the acquisition of a central target firm does not directly translate into successful network resource deployment and integration. The target's network advantages can only be fully realized when the acquirer has the ability to do so. While we find that the relative centrality of the acquirer to the target increases the acquirer's shareholder value, the significance is marginal. Essentially, the acquirer must be better positioned relative to its target to make such an acquisition work in its favor. The relatively greater centrality of the acquirer denotes its superior alliance experience, dominant power position, and status-role fit, all of which lead to a smoother transition and post-merger integration of the target's network resources. Given its marginal significance of the relative centrality, the stock market seems to value more on network synergy than on the relative network position.

This study further investigates the contextual factors that influence the value creation from the target's central position. The results show that the related deals positively moderate the relationship between the target's centrality and the acquirer's shareholder value creation. Extending beyond the general contention that the relatedness between the acquirer and the target facilitates cross-fertilization and economies of scope of the *internal* resources (Makri, Hitt, and Lane 2010), this study illustrates the synergistic potential of the network resources in related deals. This study also shows that the acquirer's prior target-industry related experience largely enhances the value extracted from a central target. Scholars have recognized the importance of the acquirer's related experiences in improving acquisition performance (Haleblian and Finkelstein 1999; Hayward 2002). This study takes a step forward in showing that the acquirer's industry-related experience improves the utilization of the target's network resources.

In our view, at least three contributions emerge from this study. First, this study contributes to the M&A literature by answering the question of how value is created for acquirers. Given that two-thirds of acquisitions fail, understanding what accounts for the performance variance of M&As remains an important question in strategy research. This study identifies the target's network position as a source of value creation for the acquirer. Furthermore, departing from previous research that mainly focuses on internally owned resources, this study highlights the synergistic potential of resources beyond a firm's boundary—network positions and network embedded resources. Such a synergy from combining externally derived resources is underexplored in M&A literature, but can be a source of value creation (Hernandez and Menon 2017). This study provides empirical evidence about the value creation of expected network synergy in M&As. It enriches the emerging research stream of network synergy in M&As (Hernandez and Menon 2017; Hernandez and Shaver 2019). Overall, the results of the study provide a more complete picture of value creation in M&As.

Second, this study advances extant M&A research by elucidating the conditions in which the acquirer is likely to benefit from the acquisition of a well-networked target. More specifically, the instrumental value of the target's network position varies depending on the acquirer's ability to exploit such a network position. Prior M&A studies tend to focus on resources of similar type between merging parties, such as resource similarity and relatedness (e.g., Kaplan and Weisbach 1992; Lubatkin 1987), as a source of synergistic combination. This study suggests that synergy can come from the combination and deployment of resources of different types, i.e., the complementarity between the acquirer's internal attributes and the target's external network positions. In other words, the acquirer's internal capabilities complement the target's external resources to derive the greatest benefits. This study suggests the complementarity of resources between merging firms as a source of synergistic gains.

Managerial Implications

This research has important managerial and practical implications. First, M&A is an important strategy to achieve firm growth. Nonetheless, M&A activities are risky endeavors known for uncertainties and high failure rates (Moeller, Schlingemann, and Stulz 2005). This study shows the strategic value of the target firm's network position in improving M&A performance. Therefore, to increase the odds of success, this study suggests that senior executives should incorporate the target firm's network positions and resources into their decision-making process. The advantageous network position occupied by a target firm denotes rich network resources that provide benefits for the acquirer. The resources beyond a target firm's boundary can be equally as important as internally owned resources in the evaluation and selection of potential target firms. Given that many resources, especially intangible and inimitable resources (e.g., trust, reputation, or implicit knowledge), are embedded in the network, the exclusion of the target's network positions and resources in the process of due diligence may result in missed opportunities for value creation. Second, this study's findings suggest that the synergistic combination of two firms' networks is value enhancing. Managers need to consider a target's network position in conjunction with the acquirer's to receive the most benefits. Specifically, acquisitions can be strategically employed to generate the greatest synergy of network positions and resources. Third, although an advantageous network position shows potential for value creation, the extent to which the acquirer capitalizes on the benefits of a target's network position is contingent on different factors, such as the type of deal and the characteristics of acquirers. Managers should carefully assess the contextual factors, such as the acquirer's internal resources and capabilities, and devise an M&A strategy that maximizes shareholder value.

Limitations and Future Research Directions

Our study has several limitations that may provide promising directions for future research. First, we examine M&A outcomes by using short-term stock price changes upon the announcement of M&A deals. This study, however, provides no indication of long-term M&A performance. We suggest that future research could explore factors that influence the acquirer's ability to integrate the target's network resources, thereby affecting long-term M&A performance. Second, we measure combined centrality as the sum of the centrality of the acquirer and the target in an M&A deal. However, it does not measure the actual centrality of the acquirer after acquisition. Thus, future research could capture the network synergy with a measure of the combined centrality after acquisitions (Hernandez and Shaver 2019). Third, we build upon social network theory for postulating the resource and positional advantages of network position. Nonetheless, we do not differentiate between the content of resources embedded in the network. These network resources may differ in type (e.g., R&D, marketing, distribution), quantity (e.g., tie strengths), or quality, which may affect the opportunities for resource redeployment and synergistic combination. Future research could further distinguish resource content embedded in the network and examine its impacts on M&A behaviors or outcomes. Fourth, we examine the type of deal and acquirer's prior industry experience as the contextual factors that influence the value creation of the target's network position. Other contextual factors, such as acquirers' internal resources and capabilities, may also play a role in affecting the value creation of the target's network resources. Future research could identify specific contexts that enable better utilization of the target's network resources.

In summary, this study offers a systematic analysis of whether and how a target firm's network position leads to the shareholder value creation of the acquirer. It demonstrates that the externally derived network position and resources of the target firm can influence the stock market's valuation of M&A deals. It also provides implications for how the acquirer manages the M&A process in driving shareholder value.

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The Competitive Effects of IPOs on Industry Peers' Finance Contracting: Evidence from Bank Loans

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Abstract

Motivation: Incumbent literature focuses on motivation, post–initial public offering (IPO) stock performance, and post-IPO operation performance. Few investigate how successful IPOs impact industry peers' performance. This paper is the first to study the competitive effects of IPOs on industry peers' bank loan terms.

Premise: Our paper investigates how a successful IPO impacts the incumbent companies' bank loan terms, including price and non-price terms. We assume that the successful IPO will affect industry peers' bank loans via escalated product market competition and financing market competition.

Approach: We select the largest IPO event in the surrounding six years in the industry to avoid contamination from other IPOs. We implement ordinary least squares (OLS) regressions on 13,075 facility-firm loan observations from 1989 to 2011. To alleviate endogenous concerns, we use difference-in-difference methodology to prove the causality between IPO competitive effects and industry peers' bank loan terms.

Results: We find that after the successful IPO, bank loans initiated for the industry's incumbent firms have significantly higher loan spread, higher likelihood of employing performance pricing provisions, and higher commitment fees. We also find that the syndicate loan structure for industry incumbents becomes more concentrated after successful IPOs in the industry: the number of lenders declines while lead bank share increases. We further show that successful IPOs' competitive effects increase as the level of industrial product competition and financing competition increase.

Conclusion: Successful IPOs impact peers' bank loan terms, including price and non-price terms. The IPO competitive effects are more pronounced among firms in more intensive industrial competition and with higher levels of information

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asymmetry. It implies that IPO competitive effects impact the peers' bank loan terms via product market competition and financing market competition.

Consistency: This paper shows that the new player in the market has a competitive advantage over incumbent firms. This finding has important implications to investors and creditors since incumbent firms comprise the majority part of capital market.

Keywords: bank loan contracts, competitive effect, financing market competition, initial public offering (IPO), product market competition

JEL Classification Codes: G14, G21, G32

INTRODUCTION

Extensive literature analyzes companies that go public. This strand of research focuses on the incentives of companies to go public, stock performance, and operation performance around initial public offerings (IPOs) (Ibbotson, Sindelar, and Ritter 1994; Loughran and Ritter 1997; Jain and Kini 1994; Chemmanur and He 2011). There are a few extant investigations into how IPOs impact the performance of industry competitors. For example, Hsu, Reed, and Rocholl (2010) show that competitive effects exist for incumbent industry peers with negative stock returns and deteriorated operating performance after a successful IPO emerges in their industry. Conversely, Akhigbe, Borde, and Whyte (2003) find no significant valuation effect of IPOs on the incumbent rival firms. Slovin, Sushka, and Polonchek (1992) suggest that the share price of commercial banks negatively reacts to industry peers' new equity issues, but this reaction does not exist for industrial firms. Debates still exist in this area, and many important questions have not been fully investigated yet, such as, In what way do successful IPOs affect their industry peers?

However, more and more anecdotal evidence reveals public reactions to the evaluations of incumbent industry peers when a new IPO enters the market. For example, when the company BigCommerce went public on August 5, 2020, its biggest competitor, Fastly's stock plunged to $108 per share from $116.18 per share. It fell further to $89.64 per share on August 6, 2020, while BigCommerce rose to $93.51 from a $24 offer price per share.[1] Investors showed huge reactions on this new player's debut. This is not an exceptional case.

The decision for a new entrant to come into the market could be attributed to several reasons. Previous literature suggests that an important determinant could be the strategic competitive position improvement from going public. Beneficial timing is also an important reason. Bayless and Chaplinsky (1996) suggest that managers take advantage of the "window of opportunity" when making equity issuance decisions. It implies that new entrants' strategy may affect their competitors' performance by enhancing their own competitive position (competitive effects). Competitive effects will cause uncertainties, including operating performance and financing risk. Valta (2012) finds that industrial competition intensity systematically increases the cost of bank loans for firms in that industry. His tests are based on the competition level of a product market, and he

[1]The price quoted is closing price cited from Yahoo Finance.

also uses changes in tariff rate as a quasi-experiment to investigate how competition shock affects the cost of loans for firms in that industry. Similarly, in our paper, IPOs could be considered a shock to industry competition. We want to investigate whether banks consider competitive effects arising from new IPOs. Specifically, we investigate whether the bank loan terms for incumbent firms are affected by the successful IPOs in their industry.

Our second goal is to study how IPOs impact the bank loan terms for industry peers. We expect incumbent industry peers will be affected via product market competition (operating performance uncertainty) and financing market competition (adverse selection).

Bank loans are very, if not the most, important financing source for firms in the United States (e.g., Graham, Li, and Qiu 2008; Chi et al. 2015).[2] It is therefore very important to know how a successful IPO affects the incumbent peers' cost of bank loans. Previous literature on bank loans mainly focuses on effects from macroeconomic conditions, firm characteristics, and industry characteristics. In this paper, we add a new dimension and examine how the strategic financing decisions, IPOs in our paper, could affect their competitors' cost of debt. We extend this strand of literature by investigating the competitive effects of IPOs on industry peers' cost of bank loans, which in turn affects the valuation of companies. We also contribute to the growing body of research on how IPOs affect their industry peers' performance.

In our paper, we use a large sample of bank loan contracts from public U.S. firms from 1989 to 2011. Following Hsu, Reed, and Rocholl (2010), we identify the largest IPOs in the surrounding six years, which means there are no larger IPOs following in the next three years. By selecting the largest IPOs, we avoid the contamination caused by overlapping IPO events. We assume that larger IPOs have the dominant effect on their competitors. Therefore, we investigate the bank loan cost of public incumbent firms around the six years of large IPOs in their industry. The results are consistent with our expectations. After IPOs emerge in the industry, the bank loan cost for incumbent public industry peers increases by 5.6 percent on average. By a series of robustness tests, we suggest that the effect of IPOs on industry peers' bank loan cost is working via two channels, competition intensity in product market and finance market moderate. We find that the IPOs' competitive effect increases as industrial product and financing competition increases. Moreover, we find that the competitive effect of IPOs on industry competitors' bank loans increases as the level of information asymmetry increases, which is consistent with the adverse selection issues coming from competition in the financing market.

Loan contracts are multi-dimensional; they are not only about loan cost. The non-price terms also contain information about the lenders' perception of borrowers' credibility. We also examine how IPOs impact the non-pricing bank loan terms, such as maturity of loans, performance pricing provisions, number of lenders, and lead bank share. We find that high-quality firms show shorter maturity after IPO events in industry, whereas medium-quality firms show lon-

[2]According to the Loan Pricing Corporation and the Federal Reserve, in 2005, the total amount of equity issued was approximately $115 billion, the total amount of corporate bonds issued was approximately $700 billion, and the total amount of bank loans issued was approximately $1,500 billion.

ger maturity. The results are consistent with previous research (Diamond 1991; Barclay and Smith 1995). Performance pricing provisions is a relatively new technique, increasingly popular with bank loans. It dynamically ties the cost of loans to firms' credit rating or other financial ratios. To some extent, the functions of performance pricing provisions overlap those of collaterals and covenants, although they cannot replace them. We believe that the employment of performance pricing provision is a good indicator for perceived default risk and information asymmetry (Asquith, Beatty, and Weber 2005). The results show that after successful IPOs in an industry, incumbents have higher rates of performance pricing provisions. We also find that commitment fees increased by about 4.3 percent for incumbent firms after large IPOs. Syndicates account for about 92 percent of bank loans in our sample. Syndicate structure is also recognized as an effective monitoring mechanism to alleviate moral hazard problems in previous literature (Bolton and Scharfstein 1996; Lee and Mullineaux 2004; Sufi 2007). The results show that after IPOs in an industry, incumbents have more concentrated syndicate structure with fewer lenders and larger lead bank shares. Finally, we perform difference-in-difference methodology to prove the causality between IPO competitive effect and industry peers' bank loan contract terms and show that after large IPOs in their industry, the treatment group paid 4.4 percent more than before.

The rest of the paper proceeds as follows. "Hypotheses Development" provides the hypotheses for our study. "Data and Sample" describes the data and summary statistics. Results, findings, and robustness tests are given in "Multivariate Analysis," followed by the conclusion.

HYPOTHESES DEVELOPMENT

Large, successful IPOs can impact industry peers' bank loan terms via two channels. First, the new IPOs are competing with incumbent firms in various aspects, e.g., market shares, human resources, and suppliers. Compared to the incumbent firms, IPOs have several advantages, such as lower debt to equity ratios, certification from an investment bank, and knowledge capital (Hsu, Reed, and Rocholl 2010). By going public, the large competitor in the industry can change the business environment and competition intensity. Previous literature suggests that intensity of competition has important implications for incumbent firms and provides evidence that the intensity of competition affects the volatility of firms' cash flow, stock returns, and the cost of debt (Gaspar and Massa 2006; Hou and Robinson 2006; Irvine and Pontiff 2009; Peress 2010; Valta 2012). Hsu, Reed, and Rocholl (2010) suggest that the operating performance of incumbent firms deteriorates after large IPOs in their industry because of new issuers' comparative advantages. Therefore, we assume that the negative impacts of IPO events on the incumbent's future cash flows and default risks will be reflected in more stringent loan contract terms because banks must invest more due diligence to monitor and assess the potential changes in creditworthiness brought by increased competition intensity.

Second, new players coming to market urge the incumbent firms to raise capital to compete against them. The fact that hot IPO markets and hot seasoned equity offering (SEO) markets cluster in time suggests that new IPOs may ignite fights among incumbent firms in the financing market. They are competing for financing sources both in public market (SEOs and bond) and private market (bank loans). Previous literature suggests that good-quality firms prefer public debts, while poor-quality firms prefer private debts (Bharath, Sunder, and Sunder 2008). This competition in the financing market exacerbates adverse selection problems because poor firms that cannot access, or find it too costly to access, a public market will borrow from a private market, making banks likely to charge more to reimburse for the increased information asymmetry risk.

Revaluation of peer firms' value is necessary after a large IPO. Consequently, information uncertainty of incumbent firms increases, which increases the cost of information asymmetry between borrowers and banks because banks must invest more in information production and due diligence to assess the potential changes in creditworthiness brought by increased information uncertainty.

The key question in this paper is whether IPOs impact the bank loan terms of their public industry peers. The bank loan terms could be measured in multiple dimensions. In this paper, we focus on the pricing terms (interest rate), and non-pricing terms, such as maturity of loans, performance pricing provisions, number of lenders, and lead bank share.

The first main hypothesis relates to the cost of bank loans. We use all-in spread drawn (AISD) as a measure of interest rate cost in bank loans. AISD is defined as the amount the borrower pays in basis points over LIBOR or LIBOR equivalent for each dollar drawn for the bank loan.

Hypothesis 1: Bank loan costs for incumbent public firms increase after a large IPO (After_IPO) *in the industry.*

Bank loan contracts consist of multiple dimensions, including both pricing terms and non-pricing terms, such as maturity, collateral requirement, number of covenants, and number of lenders. Besides increasing interest rates, lenders could secure their bank loans by imposing more stringent non-pricing terms, which are an implicit cost imposed on borrowers.

According to Diamond's (1991) theory, firms in low-risk and high-risk bands use short-term debt, because low-risk firms can refinance at lower cost, if available, while high-risk firms are not granted long-term debt because of their high default risk. In contrast, long-term debts are preferred by intermediate firms to minimize refinancing risk. We believe firms in general become riskier with the higher level of information uncertainty and information asymmetry in the post-IPO period compared to those in pre-IPO period. Therefore, we expect that firms will have shorter debt after IPOs. Barclay and Smith (1995) use contracting cost theory to explain what determines corporate debt maturity. They suggest that banks like to issue short-term debt when facing larger information asymmetries, in which case they will more frequently evaluate firms' credibility and renegotiate loan contract terms.

Hypothesis 2: The maturity of bank loans for incumbent public firms decreases after large IPOs in the industry.

Performance pricing is a relatively new loan contract term. It dynamically attaches accounting information—such as leverage, interest coverage, earnings before interest, taxes, depreciation, and amortization (EBITDA), or credit rating—to the cost of bank loans. Previous literature studies what determines the employment of performance pricing provisions and its function in loan contracts (Dichev, Beatty, and Weber 2002; Asquith, Beatty, and Weber 2005). They suggest that performance pricing provisions were developed in response to competition in the financing market, and they reduce agency cost and transaction cost. We think IPOs will increase the agency cost in bank loans due to increased information asymmetry. Performance pricing provisions could be employed to increase monitoring efficiency and reduce agency problems. Therefore, we assume that after IPOs the probability of using performance pricing provisions increase for incumbents.

Hypothesis 3: The probability of employing performance pricing provisions for incumbent firms increases after large IPOs in the industry.

Commitment fees are payments by borrowers for unused lines of credit. We focus on commitment fees, which provide firms liquidity through lines of credit. *Line of credit* is a tool for firms to soothe costs over to a good state (liquidity state) from a bad state (illiquidity state). By charging more on drawn credit and less on undrawn credit, firms self-select the usage of credit line and reach equilibrium. Berg, Saunders, and Steffen (2016) suggest that bank loan costs are underestimated by ignoring these fees. They find that relationship lending reduces commitment fees by alleviating information asymmetry concerns. We assume that increased information asymmetry of incumbent firms after IPOs in their industry will lead to higher commitment fees.

Hypothesis 4: The commitment fees for incumbent firms increase after large IPOs in the industry.

Duffie and Lando (2001) develop a theory that information risk faced by lenders is incremental to borrower default risk. Previous empirical evidence also suggests that firms with high default risk will have smaller and more concentrated syndicates to enhance monitoring incentives and facilitate renegotiation processes (Bolton and Scharfstein 1996; Lee and Mullineaux 2004). As we discussed, information uncertainty increased for industry incumbent firms after large IPOs in their industry, which increased the moral hazard concern between lead banks and participant banks. Sufi (2007) argues that information asymmetry affects the syndicate structure by making the lead arranger retain larger shares and so involve fewer lenders. In our paper, we suppose IPOs have both wealth effect and information effect on the industry peers' bank loans. Thus, we believe that after IPOs, the syndicates of incumbents will change accordingly. The fifth hypotheses are:

Hypothesis 5a: The number of lenders in syndicates for public incumbents decreases after large IPOs in their industry.

Hypothesis 5b: The lead bank share in syndicates for public incumbents increases after large IPOs in their industry.

DATA AND SAMPLE

Sample Selection

We retain IPO data from SDC New Issuer Database. Our sample includes all IPOs of nonfinancial firms in the United States between 1992 and 2008. We further exclude all non-U.S. firms to ensure IPO issuers are competing with incumbent firms in their market. To study the competitive impact of IPOs on incumbent firms, the first challenge is to select the IPOs that are least contaminated by other IPOs in the same industry. We follow the methodology used by Hsu, Reed, and Rocholl (2010) and screen out the largest IPO in the surrounding six years in each industry to ensure there are not any larger IPOs in pre- and post-three-year window around the IPO event. The IPO size is measured with IPO proceeds, and we assume larger IPOs have greater effects on incumbent firms. This selecting criterion allowed us to investigate the competitive effects of the IPOs that had the least contamination caused by smaller IPOs in the event period. In total, we obtain 107 IPO events from 1992 to 2008 for our analyses, which are relatively evenly distributed across years.[3] We also construct SEO hot/cold market indices for our robustness tests. The information on year distribution of SEOs is obtained from Jay Ritter's website.[4]

Then we obtain bank loan terms of the IPO firms' industry peers surrounding the IPO event window. We define public firms as incumbents if they have the same two-digit Standard Industrial Classification (SIC) as the IPO issuers. By doing this, we include as many observations as possible in both pre- and post-windows. The bank loan information is from Dealscan, which has detailed bank loan terms at both the facility level and deal level for both public firms and private firms. In our study, we use the facility-level loans, which are the basic unit of loans. A deal-level loan could comprise one or more facilities/tranches. These facilities under the same package could have different costs, maturity, and other bank loan terms. However, bank loan terms, such as number of lenders, may not vary across facilities for most deal-level bank loans. If a loan is syndicated, it is initiated and managed by lead banks and can involve multiple lenders as participants. Therefore, in our analyses of number of lenders and lead bank shares, we exclusively include deal-level syndicated loans.

We merge bank loan data with lagged firm characteristics from Compustat data and delete the firms with missing accounting information or loan information. We retain macroeconomic data from the Federal Reserve Board of Governors. The final pooled sample includes 13,075 facility-level loan observations from both the pre- and post-IPO periods by 6,509 incumbent firms in 57 two-digit SIC industries. Among the final sample, 6,509 loans are made in the pre-IPO period, while 6,566 facilities are made in the post-IPO period.

Table 1 contains information about sample distribution by calendar years. It shows that IPOs are distributed in a cyclic style by years, as the all-IPOs year distribution in Jay Ritter's website. But IPOs are evenly distributed in the first eight years and second eight years in our sample. Bank loans are also relatively evenly distributed across sample years. In the first 11-year period from 1989 to 1999, we

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[3]These IPOs are also relatively evenly distributed between early years and later years; there are 59 IPOs from 1992 to 1999, and 48 IPOs from 2000 to 2008.

[4]https://site.warrington.ufl.edu/ritter/ipo-data/.

TABLE 1. Sample Distributions by Year

This table presents the calendar year distribution of bank loans in column 2 and calendar year distribution of IPO events in our sample in column 3.

	Bank Loans		IPOs	
Year	Frequency	Percent	Frequency	Percent
1989	109	0.8%	—	—
1990	191	1.5%	—	—
1991	211	1.6%	—	—
1992	368	2.8%	9	8.4%
1993	483	3.7%	9	8.4%
1994	751	5.7%	7	6.5%
1995	620	4.7%	4	3.7%
1996	917	7.0%	9	8.4%
1997	1,132	8.7%	8	7.5%
1998	956	7.3%	3	2.8%
1999	937	7.2%	10	9.3%
2000	631	4.8%	2	1.9%
2001	681	5.2%	6	5.6%
2002	613	4.7%	4	3.7%
2003	555	4.2%	3	2.8%
2004	833	6.4%	2	1.9%
2005	942	7.2%	5	4.7%
2006	727	5.6%	15	14.0%
2007	689	5.3%	9	8.4%
2008	391	3.0%	2	1.9%
2009	211	1.6%	—	—
2010	122	0.9%	—	—
2011	5	0.0%	—	—
Total	**13,075**	**100%**	**107**	**100%**

have 9,678 bank loans included, and in later 11-year period from 2000 to 2010, we have 9,414 loans included. In 2011, we only have five bank loans around two IPO events due to the limited accounting information from Compustat.

Sample Description and Univariate Tests

Table 2 presents the summary statistics of bank loan contract terms and firm characteristics for the full sample, the pre-IPO subsample, and the post-IPO subsample. The last column also shows univariate tests on bank loan terms and the firms' characteristics around IPO events. The mean loan spread rises from 214 basis points over LIBOR or LIBOR equivalent to 218 basis points after an IPO event. The univariate test shows that the difference is significant at the 5 percent level. The average maturity (in months) significantly drops from 47.7 to 45.5 months after IPOs. We also find more usage of performance pricing provisions and higher numbers of financial covenants after large IPOs. These findings are consistent with previous research (Graham, Li, and Qiu 2008; Rajan and

TABLE 2. Summary Statistics and Univariate Tests

The table presents statistics of loan characteristics and firm characteristics for the sample firms. Mean, median, and standard deviation (STD) are reported for the full sample; mean and STD are shown in the sub-samples before IPOs and after IPOs. The difference between the two sub-samples is also reported. *Loan spread* is the all-in spread drawn, which is defined as the amount the borrower pays in basis point over LIBOR or LIBOR equivalent for each dollar drawn down for the bank loan. *Facilityamt* is the bank loan amount in millions of dollars. *Fincove_num* is the total count of financial covenants in loan facility. *Secured* is a dummy variable that equals one if the loan has collateral requirement. *Maturity* is the bank loans' maturity in months. *Perf pricing* is a dummy variable that equals one if the bank loan includes performance pricing provisions, and zero otherwise. *Committee* is defined as the fees payment for unused line of credit. *Lender_num* is the total number of lenders in a syndicate loan. *Leader_part* is the proportion that taken by the lead banks in a syndicate. *Current ratio* is calculated as the current assets divided by current debt. *Leverage* is total debt (long-term debt plus debt in current liabilities) divided by total assets. *Profitability* is EBITDA divided by the total assets. *Tangibility* is net property, plant, and equipment divided by total assets. *Z-score* equals (1.2 × Working capital + 1.4 × Retained earnings + 3.3 EBIT + 0.999Sales)/Total assets. *Total assets* is defined as the total assets of the firm. *Market-to-book (M/B) ratio* is the market value of equity plus book value of debt divided by total assets. Significance at 10 percent, 5 percent, and 1 percent level is indicated by *, **, and ***, respectively.

	Full Sample			Before IPOs			AfterIPOs			Difference	
Variable	N	Mean	STD	N	Mean	STD	N	Mean	STD	(Mean)	
Loan Characteristics											
Loan spread	13075	216.25	124.77	6509	214.37	124.98	6566	218.11	124.55	−3.74	**
Facilityamt	13075	248.48	496.06	6509	248.02	495.76	6566	248.93	496.40	−0.91	
Fincove_num	13075	1.68	1.49	6509	1.66	1.52	6566	1.70	1.45	−0.04	**
Secured	13075	0.76	0.43	6509	0.77	0.42	6566	0.75	0.43	0.02	**
Maturity	13075	46.57	24.25	6509	47.66	24.52	6566	45.49	23.92	2.17	***
Perf pricing	13075	0.50	0.50	6509	0.49	0.50	6566	0.52	0.50	−0.03	***
Commitfee	2319	32.49	16.53	1100	31.84	17.58	1219	33.08	15.49	−1.24	**
Lender_num	11792	8.75	6.19	5932	8.75	6.18	5860	8.75	6.19	0.00	
Leader_part	3991	29.19	23.47	2049	29.73	22.92	1942	28.61	24.04	1.12	
Firm Characteristics											
Leverage	13075	0.25	0.20	6509	0.26	0.20	6566	0.25	0.20	0.01	***
Profitability	13075	0.11	0.12	6509	0.11	0.12	6566	0.11	0.13	0.00	
Tangibility	13075	0.32	0.22	6509	0.32	0.22	6566	0.32	0.22	0.00	
Z-score	13075	1.33	1.81	6509	1.31	1.75	6566	1.35	1.87	−0.03	
Total assets	13075	1837.73	3098.71	6509	1762.33	2998.69	6566	1912.47	3193.25	−150.13	***
M/B ratio	13075	1.76	1.09	6509	1.76	1.07	6566	1.77	1.10	−0.01	

Winton 1995). Borrowers also incur higher commitment fees and annual fees. There is no significant difference in control variables in the pre- and post-IPO periods. Firms have more leverage and larger firm size after IPOs in the same industry. Although the results in univariate tests support that bank loans made by incumbent firms after large IPOs are more expensive than the loans before IPO events, these results do not consider firm characteristics that potentially cause this difference. In the following section, we will analyze the effects of IPOs on bank loan terms by controlling the firm characteristics and other relevant factors.

MULTIVARIATE ANALYSIS

In the multivariate regression analysis, we first examine the impact of large IPOs on their industry peers' bank loan cost. We further check if the competition intensity and level of information asymmetry moderate the effect of IPOs competitive effects. In this section, we also investigate how successful IPOs affect bank loan non-pricing terms for industry incumbents, such as maturity, performance pricing provisions, commitment fees, number of lenders, and lead bank share. Finally, we perform difference-in-difference analyses to prove causality.

Effects of IPOs on Cost of Bank Loan for Incumbent Firms

In this section, we use various regression models to examine the impact of IPOs on the cost of bank loans borrowed by the industry incumbents. The main empirical model is shown as below:

$$\textit{Log (All-in Spread Drawn)} = f\,(\textit{After\_IPO, Firm characteristics, Loan characteristics, Macroeconomic factors, IPO-fixed effects}) \quad (1)$$

In this regression, each observation is a facility loan borrowed by public incumbents in the IPO issuers' industry, either in the pre- or post-IPO event window. The dependent variable is the natural logarithm of the all-in spread drawn. The key independent dummy variable is *After_IPO*, which equals one if bank loans are borrowed within three years after the large IPO event, otherwise zero. We include six firm characteristics as control variables: *Leverage, Profitability, Tangibility, Z-score, Firm size,* and *Market-to-Book (M/B) ratio*. All these accounting control variables are lagged and the most recent available measurements before the facility activate date. *Leverage* represents the ratio of total debt (long-term debt plus debt in current liabilities) to total assets. *Profitability* denotes the EBITDA divided by total assets. *Tangibility* is defined as the ratio of net PPE to total assets; *Z-score* is the modified Altman's Z-score, which is a proxy for firm's financial distress. The lower Z-score, the larger default risk the firm has.[5] *Firm size* is the natural log of total assets. *M/B ratio* represents the market value of equity plus book value of debt divided by total assets.

Following previous literature on bank loans (e.g., Qian and Strahan 2007; Bharath et al. 2011; Graham, Li, and Qiu 2008), we also include loan characteristics as control variables. *Loan size* is defined as the natural logarithm of the total amount of a loan facility in millions of dollars; *Log(maturity)* is the natural logarithm of bank loans' maturity in months; *Performance pricing* is a dummy variable that equals one if the bank loan includes performance pricing provisions and zero otherwise. Instead of including year dummies, we use prevailing macroeconomic variables to control for the effect of macroeconomic cycles. *Credit spread* denotes the difference between the yields on BAA and AAA corporate bonds; *Term spread* represents the difference between the yields on 10-year and 2-year Treasury bonds. We also include the dummy variables for loan purposes and loan types as control variables.[6]

The regression results are reported in Table 3. The dependent variables in all regressions are *Log loan spread*, which is the natural logarithm of AISD. Column 1 uses *After_IPO* as the only independent variable, and the result shows that no significant difference in bank loan cost between pre- and post-IPO groups. In column 2, we add firm characteristics into the OLS regression. The coefficient on *After_IPO* is 0.0721, implying that after IPO events, borrowers on average pay 7.5 percent (= exp (0.0721) – 1) more for bank loans. We further add loan

[5]Following Graham, Li, and Qiu (2008), we use the modified Z-score, equal to (1.2 × Working capital + 1.4 × Retained earnings + 3.3 EBIT + 0.999Sales)/Total assets.

[6]We divide loan types into five categories: 364-day facility, revolver, revolver/term loan, term loan, and others. Loan purposes fall into seven categories: acquisition lines, acquisition facility, corporate purpose, debt repayment, leveraged buyout (LBO)/managed buyout (MBO), working capital, and others.

TABLE 3. The Effect of IPOs on Incumbents' Bank Loan Cost

This table presents OLS and IPO-fixed effect regression results on the effect of IPOs on their industry incumbents' bank loan price term. The dependent variable is natural log of loan spread (AISD), which is the all-in spread drawn defined as the amount the borrower pays in basis point over LIBOR or LIBOR equivalent for each dollar drawn down on the bank loan. *After_IPO* is a dummy variable that equals one if the bank loan is initiated after an IPO event in the industry. *After_IPO_y1* is defined as the first following year after IPO event in the industry. *After_IPO_y2* and *After_IPO_y3* have similar definitions. *Log(loan spread)s* is the log of all-in spread drawn (AISD), which is defined as the amount the borrower pays in basis point over LIBOR or LIBOR equivalent for each dollar drawn down for the bank loan. *Pre_firm* is an indicator that equals one if the incumbent firms only have bank loans in pre-IPO period. *Loan size* is the natural logarithm of the bank loan amount in millions of dollars. *Secured* is a dummy variable that equals one if the bank loan has a collateral requirement. Log(*maturity)* is the natural logarithm of bank loans' maturity in months. *Perf pricing* is a dummy variable that equals one if the bank loan includes performance pricing provisions, and zero otherwise. *Leverage* is total debt (long-term debt plus debt in current liabilities) divided by total assets. *Profitability* is EBITDA divided by the total assets. *Tangibility* is net property, plant, and equipment divided by total assets. *Z-score* equals (1.2 × Working capital + 1.4 × Retained earnings + 3.3 EBIT + 0.999Sales)/Total assets. *Firm size* is defined as the natural logarithm of total assets of the firm. *M/B ratio* is the market value of equity plus book value of debt divided by total assets. *Term spread* is the difference between the yields on 10-year and 2-year Treasury bonds. *Credit spread* is the difference between the yields on BAA and AAA corporate bonds. T-statistics are in parentheses. Significance at 10 percent, 5 percent, and 1 percent level is indicated by *, **, and ***, respectively. In all regressions, standard errors are adjusted for within-firm clustering.

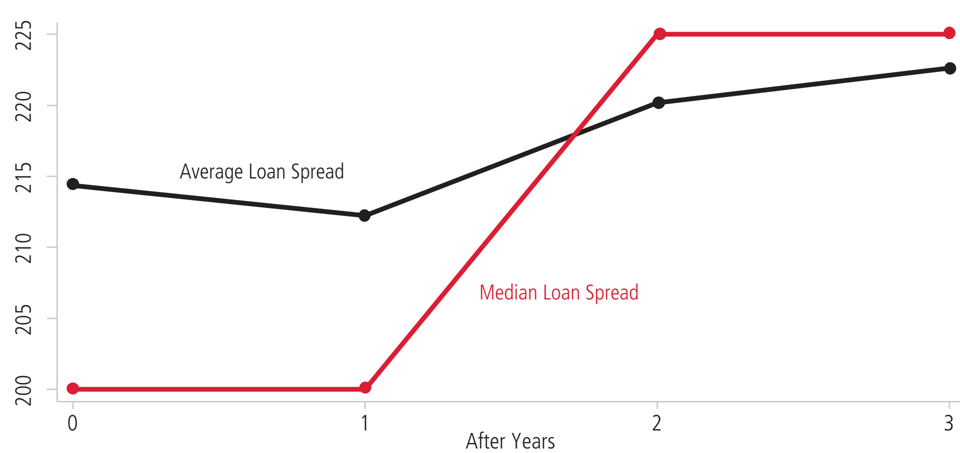
	(1)	(2)	(3)	(4)	(5)
	Log(loan spread)	Log(loan spread)	Log(loan spread)	Log(loan spread)	Log(loan spread)
After _IPO	0.0272	0.0721***	0.0239*	0.0548***	
	(0.0173)	(0.0170)	(0.0123)	(0.0128)	
Before_y3					−0.0406**
					(0.0186)
Before_y2					−0.0641***
					(0.0180)
After_IPO_y1					0.0313**
					(0.0154)
After_IPO_y2					0.0686***
					(0.0167)
After_IPO_y3					0.0732***
					(0.0175)
Firm Characteristics					
Pre_firm		0.0813***	0.0350**	0.0433**	0.0431**
		(0.0226)	(0.0176)	(0.0174)	(0.0174)
Leverage		0.832***	0.450***	0.435***	0.435***
		(0.0522)	(0.0375)	(0.0365)	(0.0365)
Profitability		−0.633***	−0.553***	−0.520***	−0.518***
		(0.0925)	(0.0642)	(0.0602)	(0.0603)
Tangibility		−0.350***	−0.112***	−0.110***	−0.110***
		(0.0467)	(0.0315)	(0.0410)	(0.0410)
Z-score		−0.0652***	−0.0294***	−0.0214***	−0.0212***
		(0.00669)	(0.00415)	(0.00416)	(0.00417)
Firm size		−0.181***	−0.0840***	−0.0978***	−0.0984***
		(0.00682)	(0.00713)	(0.00724)	(0.00723)
M/B ratio		−0.119***	−0.0542***	−0.0605***	−0.0603***
		(0.00880)	(0.00598)	(0.00585)	(0.00587)
Loan characteristics					
Loan size			−0.0465***	−0.0516***	−0.0516***
			(0.00675)	(0.00651)	(0.00650)
Secured			0.665***	0.640***	0.640***
			(0.0196)	(0.0191)	(0.0191)
Log(maturity)			−0.107***	−0.104***	−0.104***
			(0.0118)	(0.0114)	(0.0114)
Perf pricing			−0.0568***	−0.0897***	−0.0913***
			(0.0133)	(0.0135)	(0.0135)
Macro factors					
Term spread			0.0778***	0.0775***	0.0758***
			(0.00631)	(0.00640)	(0.00637)
Credit spread			0.229***	0.163***	0.159***
			(0.0217)	(0.0223)	(0.0224)
Control for					
Loan type	No	No	Yes	Yes	Yes
Loan purpose	No	No	Yes	Yes	Yes
IPO-fixed effects	No	No	No	Yes	Yes
Observations	13075	13075	13075	13075	13075
Adjusted R^2	0.000	0.340	0.593	0.613	0.614

characteristics and macroeconomic controls in OLS regression. The results in column 3 show the coefficient on *After_IPO* is still significant.

To avoid bias due to omitted variables that are correlated with IPO events, we use IPO-fixed effects regression in column 4 and column 5. In column 4, we still use *After_IPO* as the key independent variable, and the coefficient is 0.0548 and is significant at the 1 percent level. It implies that, holding other variables constant, after a large IPO in the same industry, borrowers pay about 12 basis points more for bank loans.[7] To investigate how the IPO competitive effects evolve with time, we divide post-IPO groups into three different groups. *After_IPO_y1* is a dummy variable that equals one if the bank loan facility is initiated within one year after IPO events in the same industry.[8] Similarly, *After_IPO_y2* and *After_IPO_y3* represent facilities initiated within the second and third years, respectively. The results are shown in column 5 of Table 3. We can see that there is a clear monotonic increasing trend of IPO impacts on bank loans. The coefficient on *After_IPO_y1* is about 0.031, while those on *After_IPO_y2* and *After_IPO_y3* are about 0.069 and 0.073, respectively. It implies that the effect of IPOs on bank loan cost is reinforcing over time. Figure 1 shows how loan spread changes by year. It shows that in the first year, the loan spread decreases slightly from 214 basis points over LIBOR before IPO events to 212 basis points in the year following IPO events, then roars to 220 basis points in the second year, then further increases to 222 basis points in the third year after IPO events. An interesting point is that the statistical graph shows that on average loan spread decreases in the first year after large IPOs in the same industry. This may be due to the lagging competitive effects that IPO events have on the industry peers. Another possible reason is that an IPO event in the same industry is a positive signal for the whole industry or even the whole economy (during the hot IPO market). However, after controlling the firm characteristics, macroeconomic factors, and IPO-fixed effects, results in column 4 and column 5 show that IPO events still impose positive effects on

FIGURE 1. Loan Spread Year Trend after IPO

This figure shows how loan spread changes over time around IPO events. The y axis is the AISD. The x axis is the timeline denoting the years, with time 0 representing the year of IPO event. The black line denotes the average loan spread for all incumbent firms by years. The red line shows how median AISD change by years after IPO event.



[7]The coefficient is 0.0548, means that ceteris paribus, After_IPO large IPO event, bank loan cost increase by about 5.6 percent (exp (0.0548) – 1). It means it increase 12.08 basis points (5.6% × 214.37).

[8]We also use industry-fixed effects in robustness tests. The results are similar to IPO-fixed effects models.

bank loan cost. In the following section, we investigate how competition intensity and information asymmetry moderate the competitive effects of IPO events, and through which channels the IPO affects incumbents' bank loans.

Competitive Effects of IPOs and Competition Intensity

In this section, we investigate how competition in the product and financing markets moderate the impact of IPOs on incumbent firms. We use Herfindahl-Hirschman Index (HHI) as a measurement for industry concentration. *HM_HHI* is an indicator variable that equals one when the firm belongs to high or moderate HHI industry.[9] We also include moderate industry firms as *HM_HHI* group because there are only a few facilities, 461 and 622 facilities are borrowed by firms in high and moderate HHI firms, respectively. By interacting *HM_HHI* with the *After_IPO* variable, we know how competition moderates the effect of IPOs on industry peers' bank loan cost. The results are show in Table 4 column 1. The coefficients show that on average firms in high/moderately concentrated industry have higher bank loan cost, and after IPOs, these firms incur higher increasing effect on bank loans than the firms in the mildly concentrated industries. The results are consistent with previous literature (Hsu, Reed, and Rocholl 2010). When IPO firms come into the market, the industry incumbent deteriorates in operating performance. We show that this negative effect is reinforced by competition.

We further investigate whether the competition in financing market moderate the effect of IPO events on industry peers' bank loans. We use seasoned equity offerings (SEOs) hot market index as a proxy for competition in the financing market. SEOs are new equity issuance by already-public firms. When a hot SEO market occurs, investors flood to SEO issuers, making it more difficult for industry peers to raise capital to compete against both the new players in the market (IPO issuers) and high-quality competitors in the industry (SEO issuers). On the other side, as previous SEO models argue that hot market issuers are of better quality on average (Choe et. al. 1993; Bayless and Chaplinsky 1996), when a hot SEO market occurs, we expect incumbent firms to pay a higher loan cost compared to those in neutral/cold markets. The results are shown in column 2 of Table 4. Following Bayless and Chaplinsky (1996), we define a hot SEO by issue volume. The key independent variable *After_IPO_hot* is an indicator that equals one if the market is a hot SEO market after a large IPO event, and zero otherwise. *After_IPO_cold* is is an indicator that equals one if the market is a cold SEO market after a large IPO event, and zero otherwise. The coefficient on *After_IPO_hot* is 0.0571, implying that after an IPO event in a hot SEO market, the bank loan costs increase by about 5.9 percent, while the impact in a cold SEO market is not statistically significant.

A second proxy we use for measuring the competition intensity in the financing market is industry median underpricing. Lowry and Schwert (2002) suggest that underpricing reflects the information learned during the registration period and positive information results in higher underpricing. Therefore, we

[9]The Department of Justice considers industries to be concentrated if the Herfindahl-Hirschman index is greater than 2,500, and to be moderately concentrated if the Herfindahl-Hirschman index is between 1,500 and 1,800.The detailed information is on website: http://www.usdoj.gov/atr/public/testimony/hhi.htm.

TABLE 4. IPOs' Competitive Effects and Competition Intensity

This table presents IPO-fixed effect regression results on the effect of IPOs on their industry incumbents' bank loan price term. The dependent variable is natural log of loan spread (AISD), which is the all-in spread drawn defined as the amount the borrower pays in basis point over LIBOR or LIBOR equivalent for each dollar drawn down on the bank loan. *After_IPO* HM_HHI* is an interaction term of *After_IPO* and *HM_HHI. HM_HHI* is a dummy variable that equals one if the incumbent firms are in high or moderately concentrated industry. After_IPO_hot is an interaction term of *After_IPO and Hot SEO market*. *Hot SEO market* is a dummy variable that equals one if loan active date in in hot SEO market defined by SEO volume. *After_IPO_cold* has similar definition. It's an interaction term of *After_IPO and cold SEO market*. *After_IPO*High_underpricing* is an interaction term of *After_IPO* and *High_underpricing. High_underpricing* is an indicator that equals one if the incumbent firm is in an industry with high median underpricing. *Log(loan spread)* is the log of all-in spread drawn (AISD), which is defined as the amount the borrower pays in basis point over LIBOR or LIBOR equivalent for each dollar drawn down on the bank loan. *Pre_firm* is an indicator that equals one if the incumbent firms only have bank loans in pre-IPO period. *Loan size* is the natural logarithm of bank loan amount in millions of dollars. *Secured* is a dummy variable that equals one if the bank loan has a collateral requirement. *Log(maturity)* is the natural logarithm of bank loans' maturity in months. *Perf pricing* is a dummy variable that equals one if the bank loan includes performance pricing provisions, and zero otherwise. *Leverage* is total debt (long-term debt plus debt in current liabilities) divided by total assets. *Profitability* is EBITDA divided by the total assets. *Tangibility* is net property, plant, and equipment divided by total assets. *Z-score* equals (1.2 × Working capital + 1.4 × Retained earnings + 3.3 EBIT + 0.999Sales)/Total assets. *Firm size* is defined as the natural logarithm of total assets of the firm. *M/B ratio* is the market value of equity plus book value of debt divided by total assets. *Term spread* is the difference between the yields on 10-year and 2-year Treasury bonds *Credit spread* is the difference between the yields on BAA and AAA corporate bonds. T-statistics are in parentheses. Significance at 10 percent, 5 percent, and 1 percent level is indicated by *, **, and ***, respectively. In all regressions, standard errors are adjusted for within-firm clustering.

	(1)	(2)	(3)	(4)
	Log(loan spread)	Log(loan spread)	Log(loan spread)	Log(loan spread)
After_IPO	0.0550***	0.0681***		0.0548***
	(0.0132)	(0.0166)		(0.0154)
HM_HHI	0.0830*			
	(0.0463)			
After_IPO* HM_HHI	0.137***			
	0.0830*			
Decrease_HHI		0.0219		
		(0.0177)		
After_IPO*Decrease_HHI		0.0632***		
		(0.0178)		
After_IPO_hot			0.0571***	
			(0.0164)	
After_IPO_cold			−0.0111	
			(0.0252)	
High_underpricing				0.0204
				(0.0178)
After_IPO*High_underpricing				0.0746***
				(0.0181)
Pre_firm	0.0427**	0.0425**	0.0235	0.0438**
	(0.0173)	(0.0174)	(0.0160)	(0.0174)
Leverage	0.433***	0.435***	0.428***	0.436***
	(0.0366)	(0.0365)	(0.0366)	(0.0366)
Profitability	−0.525***	−0.522***	−0.529***	−0.521***
	(0.0602)	(0.0602)	(0.0602)	(0.0603)
Tangibility	−0.111***	−0.111***	−0.115***	−0.111***
	(0.0410)	(0.0410)	(0.0410)	(0.0409)
Z-score	−0.0215***	−0.0214***	−0.0214***	−0.0214***
	(0.00415)	(0.00416)	(0.00416)	(0.00417)
Firm size	−0.0992***	−0.0978***	−0.0969***	−0.0979***
	(0.00725)	(0.00723)	(0.00724)	(0.00726)
M/B ratio	−0.0601***	−0.0605***	−0.0596***	−0.0605***
	(0.00584)	(0.00585)	(0.00584)	(0.00585)

(continued)

TABLE 4. IPOs' Competitive Effects and Competition Intensity *(continued)*

	(1)	(2)	(3)	(4)
	Log(loan spread)	Log(loan spread)	Log(loan spread)	Log(loan spread)
Loan size	–0.0522***	–0.0517***	–0.0518***	–0.0516***
	(0.00650)	(0.00651)	(0.00651)	(0.00651)
Secured	0.640***	0.640***	0.641***	0.640***
	(0.0191)	(0.0191)	(0.0191)	(0.0191)
Log(maturity)	–0.104***	–0.104***	–0.103***	–0.103***
	(0.0114)	(0.0114)	(0.0114)	(0.0114)
Perf pricing	–0.0904***	–0.0899***	–0.0879***	–0.0894***
	(0.0135)	(0.0135)	(0.0135)	(0.0135)
Term spread	0.0770***	0.0765***	0.0806***	0.0779***
	(0.00640)	(0.00646)	(0.00659)	(0.00638)
Credit spread	0.164***	0.163***	0.179***	0.164***
	(0.0223)	(0.0222)	(0.0232)	(0.0223)
Control for				
Loan type	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
IPO-fixed effects	Yes	Yes	Yes	Yes
N	13075	13075	13075	13075
Adjusted R^2	0.613	0.614	0.613	0.614

assume that higher median underpricing implies more positive information about the IPO issuers and more severe competition for incumbents, making it harder for incumbent firms to obtain bank loans at lower prices. The results are shown in column 3 of Table 4. In general, incumbent firms pay about 5.6 percent more to obtain loans after large IPOs; however they pay about 7.7 percent more if the IPOs occur with high IPO initial returns.

Competitive Effects of IPOs and Information Asymmetry

We are also curious about how firm-specific information asymmetry would moderate the effect of large IPOs on industry peers' bank loan cost. As discussed, IPOs affect industry competitors' bank loan terms via two channels: information uncertainty and information asymmetry.

Bharath, Sunder, and Sunder (2008) suggest that prior relation helps alleviate information asymmetry between borrowers and lenders and reduces the adverse selection cost for banks to screen out the poor-quality firms. We interact *Piror_relaiton* with *After_IPO* to find out if relationship lending alleviates the negative effects of IPOs on incumbent firms' bank loan cost. The results are show in column 1 of Table 5. The coefficient on the interaction term is 0.0407 compared to 0.0467 on *After_IPO*, implying that bank loan costs increase less after IPO events for firms with prior lending relationships with banks. Consistent with previous literature (Sharp 1990), the coefficient on *Prior_relation* is –0.036, also suggesting firms with prior relations have lower loan costs.

Duffie and Lando (2001) develop a theory that information risk faced by lenders is incremental to borrower default risk. We assume that firms' informa-

TABLE 5. IPOs' Competitive Effects and Information Asymmetry

This table presents IPO-fixed effect regression results on the effect of IPOs on their industry incumbents' bank loan price term. The dependent variable is *Log(loan spread)*, which is the natural log of loan spread (AISD), which is the all-in spread drawn defined as the amount the borrower pays in basis point over LIBOR or LIBOR equivalent for each dollar drawn down for the bank loan. *After_IPO*Prior_relation* is an interaction term of *After_IPO* and *Prior_relation*. *Prior_relation* is a dummy variable that equals one if the borrowers have a lending relationship with the lead bank before the IPO. *After_IPO*Fdistressed* is an interaction term of *After_IPO and Fdistressed*. *Fdistressed* is a dummy variable that equals one when borrower has negative net income or net operating cash flow. *After_IPO*Bigfirm* is an interaction term of *After_IPO* and *Bigfirm*. *Bigfirm* is an indicator that equals one if the incumbent firm is in the top tercile as ranked by total assets. *Log(loan spread)* is the log of all-in spread drawn (AISD), which is defined as the amount the borrower pays in basis point over LIBOR or LIBOR equivalent for each dollar drawn down for the bank loan. *Pre_firm* is an indicator that equals one if the incumbent firms only have bank loans in the pre-IPO period. *Loan size* is the natural logarithm of bank loan amount in millions of dollars. *Secured* is a dummy variable that equals one if the bank loan has a collateral requirement. *Log(maturity)* is the natural logarithm of bank loans' maturity in months. *Perf pricing* is a dummy variable that equals one if the bank loan includes performance pricing provisions, and zero otherwise. *Leverage* is total debt (long-term debt plus debt in current liabilities) divided by total assets. *Profitability* is EBITDA divided by the total assets. *Tangibility* is net property, plant, and equipment divided by total assets. *Z-score* equals (1.2 × Working capital + 1.4 × Retained earnings + 3.3 EBIT + 0.999Sales)/Total assets. *Firm size* is defined as the natural logarithm of total assets of the firm. *M/B ratio* is the market value of equity plus book value of debt divided by total assets. *Term spread* is the difference between the yields on 10-year and 2-year Treasury bonds. *Credit spread* is the difference between the yields on BAA and AAA corporate bonds. T-statistics are in parentheses. Significance at 10 percent, 5 percent, and 1 percent level is indicated by *, **, and ***, respectively. In all regressions, standard errors are adjusted for within-firm clustering.

	(1)	(2)	(3)
	Log(loan spread)	Log(loan spread)	Log(loan spread)
After_IPO*Prior_relation			
0 1	−0.0360**		
	(0.0152)		
1 0	0.0467***		
	(0.0156)		
1 1	0.0407**		
	(0.0171)		
After_IPO*Fdistressed			
0 1		0.188***	
		(0.0163)	
1 0		0.0755***	
		(0.0158)	
1 1		0.200***	
		(0.0182)	
After_IPO*Bigfirm			
0 1			−0.0193
			(0.0221)
1 0			0.0411***
			(0.0158)
1 1			0.0475**
			(0.0228)
Pre_firms	0.0395**	0.0326*	0.0392**
	(0.0176)	(0.0172)	(0.0177)
Leverage	0.433***	0.419***	0.436***
	(0.0352)	(0.0362)	(0.0365)
Profitability	−0.505***	−0.353***	−0.523***
	(0.0594)	(0.0602)	(0.0602)
Tangibility	−0.104***	−0.0868**	−0.111***
	(0.0386)	(0.0405)	(0.0409)
Z-score	−0.0217***	−0.0198***	−0.0214***
	(0.00411)	(0.00404)	(0.00417)

(continued)

TABLE 5. IPOs' Competitive Effects and Information Asymmetry *(continued)*

	(1)	(2)	(3)
	Log(loan spread)	Log(loan spread)	Log(loan spread)
Firm size	−0.0946***	−0.0975***	−0.0964***
	(0.00667)	(0.00705)	(0.00865)
M/B ratio	−0.0615***	−0.0561***	−0.0603***
	(0.00575)	(0.00573)	(0.00586)
Loan size	−0.0499***	−0.0512***	−0.0516***
	(0.00612)	(0.00641)	(0.00651)
Secured	0.653***	0.615***	0.641***
	(0.0189)	(0.0191)	(0.0191)
Log(maturity)	−0.104***	−0.0963***	−0.104***
	(0.0111)	(0.0112)	(0.0114)
Perf pricing	−0.0987***	−0.0810***	−0.0895***
	(0.0132)	(0.0133)	(0.0135)
Term spread	0.0769***	0.0781***	0.0775***
	(0.00636)	(0.00632)	(0.00639)
Credit spread	0.179***	0.159***	0.161***
	(0.0217)	(0.0221)	(0.0223)
Control for			
Loan type	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes
IPO-fixed effects	Yes	Yes	Yes
N	12760	13075	13075
Adjusted R^2	0.622	0.622	0.613

tion asymmetry increases with financial distress. The second proxy we use is financial distress. *Fdistressed* is a dummy variable that equals one if the firm has negative net income or negative operating cash flows. The results are shown in column 2 of Table 5. We can see that although on average financially distressed firms have higher costs for bank loans, these firms pay even more after IPOs in their industries. The coefficient on the interaction term is 0.2 at the 1 percent significance level, implying about a 22 percent increase in bank loan costs for financially distressed incumbent firms, compared with about a 7.8 percent increase for non-financially distressed firms. The economic significance is very high.

Finally, following previous literature, we use firm size as a proxy for information asymmetry. Larger firms have lower levels of information asymmetry. The results in column 3 of Table 5 suggest that large firms incur slightly higher impact of IPOs' competitive effects by 0.7 percent (4.9 percent versus 4.2 percent). A possible reason is that big firms, rather than the small firms, are the major competitors against the new player in town. It is the group of big firms that have the largest incremental information uncertainty, which makes banks charge more to reimburse the cost of information processing.

Effect of IPOs on Non-Pricing Terms of Bank Loans

Bank loan contracts are not only about cost, but an assembly of terms in multiple dimensions. These non-pricing terms could also impose implicit costs on borrowers. If the IPOs convey information about a company's future operating performance or performance distribution, then it could also affect other terms in the contract, such as loan maturity, employment of performance pricing provisions, and syndicate structure. In this section, we will study the effect large IPO events have on industry incumbents' non-pricing bank loan terms.

Debt Maturity

Column 1 in Table 6 shows the results of IPOs on the maturity of industry incumbents' bank loans. In contrast with the univariate test result, after controlling other related variables, the coefficient on *After_IPO* is not significant. As previously discussed, high-, medium-, and low-quality firms have different preferences for loan maturity. We further divide incumbent firms into three groups according to firm size (Bharath et al. 2011) and examine the impact of IPOs on bank loan terms of these three groups separately. *High_quality* equals one if the borrower is in the top tercile as ranked by firm size. *Med_quality* and *Low_quality* denote firms in the medium tercile and lowest tercile, respectively. The results are reported in column 2 of Table 6. Contrary to our hypothesis, the medium-quality firms have even longer maturity after large IPO events, while the high-quality firms tend to have shorter maturity. More tests should be done for explaining this abnormal phenomenon.

In regression, we also control for *Log asset maturity*, which is the weighted average of maturity of current assets and net PPE.[10] The coefficient on *Log asset maturity* is positively correlated with loan maturity, significant at the 10 percent level. Other controls—such as leverage, profitability, loan size, and Z-score—are positively correlated with loan maturity, which is consistent with the empirical evidence in previous literature by Barclay and Smith (1995), Johnson (2003), and Graham, Li, and Qiu (2008). Further, macroeconomic controls term spread and credit spread are negatively correlated with loan maturity, implying that, on average, loan maturities are shorter in bad times.

Performance Pricing Provisions

Performance pricing is a relatively new provision in loan contracts that dynamically determines the loan price according to the borrowers' credit rating or financial performance. As Asquith, Beatty, and Weber (2005) point out, performance pricing provisions in syndicated loans alleviate the concerns of moral hazard costs. Column 3 of Table 6 shows probit regression results with *performance pricing* as the dependent variable that equals one if the bank loan uses performance pricing provisions. The results show that performance pricing provisions are more likely to be employed after large IPOs in the industry. The coefficient is 0.271, significant at the 1 percent level, denoting an average of 10.8 percent

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[10]We follow the definition provided by Barclay, Marx, and Smith (2003) to estimate *Asset Maturity*.
The equation is: $\frac{CA}{CA+NPPE} \times \frac{CA}{COGS} + \frac{NPPE}{CA+NPPE} \times \frac{NPPE}{Depreciation}$.

TABLE 6. IPOs' Competitive Effects on Non-Pricing Bank Loan Terms

This table presents IPO-fixed effect regression results on the effect of IPOs on their industry incumbents' bank loan price term. The dependent variables in column 1 and column 2 are *Log(maturity)*, which is the natural logarithm of bank loans' maturity in months. The dependent variable in column 3 is *Performance pricing*, which is defined as a dummy variable that equals one if the bank loan includes performance pricing provisions, and zero otherwise. The dependent variable in column 4 is *Log commitfees*, which is the natural logarithm of commitment fees in bank loans. *After _IPO* is a dummy variable that equals one if the bank loan is initiated after an IPO event in the industry. *After_IPO_high* is an interaction term of *After_IPO* and *High quality*. *High quality* is a dummy variable that equals one if the firm is in the top tercile as ranked by total assets; *After_IPO_medium* and *After_IPO_low* have similar definitions. *Pre_firm* is an indicator that equals one if the incumbent firms only have bank loans in the pre-IPO period. *Loan size* is the natural logarithm of the bank loan amount in millions of dollars. *Secured* is a dummy variable that equals one if the bank loan has a collateral requirement. *Leverage* is total debt (long-term debt plus debt in current liabilities) divided by total assets. *Profitability* is EBITDA divided by the total assets. *Tangibility* is net property, plant, and equipment divided by total assets. *Z-score* equals (1.2 × Working capital + 1.4 × Retained earnings + 3.3 EBIT + 0.999Sales)/Total assets. *Firm size* is defined as the natural logarithm of total assets of the firm. *M/B ratio* is the market value of equity plus book value of debt divided by total assets. *Term spread* is the difference between the yields on 10-year and 2-year Treasury bonds. *Credit spread* is the difference between the yields on BAA and AAA corporate bonds. T-statistics are in parentheses. Significance at 10 percent, 5 percent, and 1 percent level is indicated by *, **, and ***, respectively. In all regressions, standard errors are adjusted for within-firm clustering.

	(1)	(2)	(3)	(4)
	Log(maturity)	Log(maturity)	Performance pricing	Log (commitfees)
After_IPO	0.00620		0.271***	0.0423**
	(0.0118)		(0.0385)	(0.0187)
After_IPO_high		−0.0599***		
		(0.0208)		
After_IPO_medium		0.0286*		
		(0.0148)		
After_IPO_low		−0.0203		
		(0.0172)		
Pre_firm	−0.0223	−0.0175	−0.161***	−0.00132
	(0.0185)	(0.0188)	(0.0555)	(0.0333)
Log(asset maturity)	0.0262*	0.0293*		
	(0.0154)	(0.0153)		
Leverage	0.326***	0.300***	0.134	0.253***
	(0.0366)	(0.0364)	(0.111)	(0.0589)
Profitability	0.353***	0.371***	1.446***	−0.133
	(0.0689)	(0.0701)	(0.237)	(0.151)
Tangibility	0.00799	−0.0556	−0.244**	−0.168***
	(0.0389)	(0.0515)	(0.120)	(0.0603)
Z-score	0.00995*	0.00871*	0.0512***	−0.0358***
	(0.00516)	(0.00522)	(0.0168)	(0.0107)
Firm size	−0.0205***	−0.0158**	−0.0911***	−0.0151
	(0.00666)	(0.00711)	(0.0194)	(0.0106)
M/B ratio	−0.00534	−0.00514	−0.0202	−0.0341***
	(0.00551)	(0.00553)	(0.0189)	(0.0118)
Loan size	0.103***	0.101***	0.244***	−0.0390***
	(0.00654)	(0.00658)	(0.0181)	(0.0112)
Secured	0.0580***	0.0544***	−0.293***	0.324***
	(0.0151)	(0.0151)	(0.0474)	(0.0224)
Term spread	−0.0290***	−0.0277***	−0.0936***	0.0882***
	(0.00604)	(0.00609)	(0.0187)	(0.00910)
Credit spread	−0.157***	−0.158***	−0.127**	0.110***
	(0.0212)	(0.0213)	(0.0182)	(0.0305)

(continued)

TABLE 6. IPOs' Competitive Effects on Non-Pricing Bank Loan Terms *(continued)*

	(1)	(2)	(3)	(4)
	Log(maturity)	Log(maturity)	Performance pricing	Log (commitfees)
Log(maturity)			0.628***	
			(0.0314)	
Performance pricing				0.215***
				(0.0832)
Control for				
Loan type	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
IPO-fixed effects	Yes	Yes	Yes	Yes
N	12979	12979	13071	2319
Adjusted R^2/Adjusted McFadden R^2	0.424	0.426	0.261	0.400

marginal effect of IPOs on the likelihood of using performance pricing provision. This result is consistent with our hypothesis that after successful IPOs, incumbent firms are more likely to experience deteriorating operation performance and increased default risk. To reduce agency cost and transaction cost, banks tend to use performance pricing provisions as a monitoring mechanism after IPOs in the industry.

The effects of control variables on performance pricing are very interesting. They show profitable firms with less default risk are more likely to use performance pricing provisions, probably because performance pricing provisions are typically used to increase credit improvements (Dichev, Beatty, and Weber 2002). If a firm has more tangible assets, or uses collaterals, they are less likely to use performance pricing provisions. These firms are considered high quality with less default risk, thus reducing the incentives to use performance pricing provisions. It also shows that large loans with longer maturity tend to use performance pricing provisions, which is consistent with previous studies about the reducing transaction costs. Finally, credit risk is positively correlated with employment of performance pricing provisions, while terms spread is negatively associated with it. In bad years, banks are more likely to use performance pricing provisions.

Commitment Fees

Berg, Saunders, and Steffen (2013) point out that fee payments are an indispensable part of bank loan costs. They suggest that relationship lending reduces the fee payments via helping to overcome the information asymmetry and moral hazard issues. In this section, we examine if large IPO events will pose negative effects on commitment fees by increasing firms' information asymmetry. The result is shown in column 4 of Table 6. The dependent variable is *Log commitfee*, which is the natural logarithm of commitment fees. Commitment fees are the fees paid by firms for unused lines of credit. The coefficient of *After_IPO* is 0.0423, significant at the 5 percent level. It implies that after large IPO events, incumbent firms pay about 4.3 percent more for commitment fees. The coefficients on control variables show that firms with higher leverage, lower profitability, lower M/B ratio, and lower Z-score pay more commitment fees, which is consistent with previous literature.

Syndicate Loan Structure

Previous literature suggests that operating performance of incumbents deteriorates after large IPOs in the industry. We believe that default risk increases with deteriorating operating performance. A syndicate loan is provided by a group of banks and/or financial institutions, and is managed and supervised by a lead bank, which is also referred to as a *lead arranger.* Sufi (2007) suggests that syndicated loans are of more concentrated structure when moral hazard cost is high. In this section, we investigate the effects of large IPOs on industry peers' syndicate structure. Specifically, we examine the number of lenders in a syndicate and the proportion the lead bank invested in a syndicate.

Number of Lenders

Column 3 of Table 7 shows that after IPOs, the syndicate loans of incumbents have fewer lenders involved. The coefficient is –0.113, denoting that after IPOs, the number of lenders decreases by about 11 percent and the marginal effect on the number of lenders is about 0.64 less. The result is consistent with our hypothesis. It also shows that larger firms with higher profitability tend to have syndicates with more lenders. This may be because these firms have less default risk and less moral hazard concerns, therefore more lenders are attracted to their syndicates. Firms with higher leverage have more lenders, which is contrary to our expectation. Perhaps this occurs because leverage is positively associated with the total loan size that a firm borrows, and loan size is positively associated with number of lenders. These results also show that long-term loans have more lenders. This is quite intuitive and consistent with the purpose of syndicates: to share risk. Terms spread is positively correlated with number of lenders, while credit spread is negatively associated with it. When long-term interest rates increase, more banks like to participate in loans and share the profit. High credit spread may imply higher information asymmetry risk between good firms and bad firms. There are two possible explanations why credit risk is negatively correlated with number of lenders. One is that concentrated syndicate structure relieves the moral hazard concern. The alternative explanation is that lead banks are reluctant to share the profit with other banks in a syndicate when the reimbursement of credit quality increases.

Lead Bank Share

Column 2 of Table 7 reports the multi-regression results for lead bank share. The dependent variable is *Log leader part,* which is the natural logarithm of lead bank share in syndicated loans. The coefficient is 0.0599, denoting that after IPOs in the industry, lead bank shares increase by 6.0 percent at a 5 percent significance level. The result is consistent with our hypothesis. As we expected, incumbents have higher default risk and information asymmetry after successful IPOs in the industry. Therefore, lead banks are required to take larger share in a syndicate to increase the incentives to monitor borrowers and avoid moral hazard issues.

The coefficients on control variables indicate that the lead bank takes a larger portion in a syndicate for larger firms with lower leverage, which is con-

TABLE 7. IPOs' Competitive Effects on Syndicated Loan Structure

This table presents IPO-fixed effect regression results on the effect of IPOs on their industry incumbents' bank loan price term. The dependent variable in column 1 is *lender number,* which is the total count of lenders in a syndicated loan. The dependent variable in column 2 is *Log leader part,* which is the total shares owned by lead banks in a syndicated loan. *After_IPO* is a dummy variable that equals one if the bank loan is initiated after an IPO event in the industry. *Pre_firm* is an indicator that equals one if the incumbent firms only have bank loans in the pre-IPO period. *Loan size* is the natural logarithm of bank loan amount in millions of dollars. *Secured* is a dummy variable that equals one if the bank loan has a collateral requirement. *Leverage* is total debt (long-term debt plus debt in current liabilities) divided by total assets. *Profitability* is EBITDA divided by the total assets. *Tangibility* is net property, plant, and equipment divided by total assets. *Z-score* equals (1.2 × Working capital + 1.4 × Retained earnings + 3.3 EBIT + 0.999Sales)/Total assets. *Firm size* is defined as the natural logarithm of total assets of the firm. *M/B ratio* is the market value of equity plus book value of debt divided by total assets. *Term spread* is the difference between the yields on 10-year and 2-year Treasury bonds. *Credit spread* is the difference between the yields on BAA and AAA corporate bonds. T-statistics are in parentheses. Significance at 10 percent, 5 percent, and 1 percent level is indicated by *, **, and ***, respectively. In all regressions, standard errors are adjusted for within-firm clustering.

	(1)	(2)
	Lender number	Log leader part
After_IPO	−0.113***	0.0599**
	(0.0160)	(0.0236)
Pre_firm	−0.0540*	−0.0127
	(0.0293)	(0.0366)
Leverage	0.184***	−0.204**
	(0.0531)	(0.0813)
Profitability	0.670***	0.130
	(0.128)	(0.203)
Tangibility	−0.0513	−0.00778
	(0.0543)	(0.0831)
Z-score	−0.0115	−0.00869
	(0.00873)	(0.0157)
Firm size	0.168***	−0.113***
	(0.0100)	(0.0146)
M/B ratio	−0.00404	−0.0109
	(0.00931)	(0.0133)
Loan size	0.279***	−0.246***
	(0.0110)	(0.0169)
Secured	0.0368**	0.00858
	(0.0184)	(0.0280)
Log(maturity)	0.271***	−0.192***
	(0.0217)	(0.0270)
Performance pricing	0.232***	−0.149***
	(0.0186)	(0.0311)
Term spread	0.0560***	−0.0288**
	(0.00784)	(0.0119)
Credit spread	−0.0556**	0.127***
	(0.0250)	(0.0402)
Loan type	Yes	Yes
Loan purpose	Yes	Yes
IPO-fixed effects	Yes	Yes
N	7345	2969
Adjusted R^2/McFadden's adjusted R^2	0.143	0.508

sistent with our discussion above. Larger loans with longer maturity tend to show less lead bank share, which is intuitive with respect to risk sharing. Terms spread is negatively correlated with lead bank share, suggesting the lead bank is reluctant to take large share for lower return of loan maturity. Consistent with the number of lender analyses, credit spread is positively associated with lead bank share, denoting that the lead bank likes to take a larger share and enjoy the profit when return for credit risk increases, or due to the increasing moral hazard risk.

Differences-in-Difference Tests

Our empirical tests above establish significant support that after large IPOs, incumbent firms have higher bank loan cost, more frequent use of performance pricing provisions, higher annual commitment fees, and more concentrated syndicate loan structure. However, the causality concern still exists. There may be some omitted variables that are correlated with IPO events, but not controlled in our regressions. To make solid causal inferences, we use difference-in-difference methodology by using large IPO events as a quasi-treatment. To construct the treatment group, we select out firms in each industry that have bank loans in both pre- and post-IPO periods. The control group is selected out of firms that don't incur any large IPO effect, which means they don't have large IPO events around their bank loan initiations. To match control firms with treatment firms, we use several criteria, as follows:

1. The matching firms could not be of the same 2-digit SIC as the treated firms.
2. The matching firms are of same fiscal year as treated firms.
3. The firm size and Z-score ratio of matching firm falls into the range of 1.2 to 0.8 of those of the treated firms.
4. The nearest three neighbors around the M/B ratio of treated firms was selected.

By using this screening procedure, we ensure that the matching sample is not the same industry as the treated group, but has similar relevant firm characteristics. We select the nearest three neighbors rather than the closest neighbor, because after merging with bank loan information, we will lose observation by deleting matching firms with only pre- or post-IPO bank loans. The final sample is quite balanced. Among 28,246 facilities, 13,312 are pre-IPO facilities, while 14,934 facilities are post-IPO observations; 14,633 belong to the control group and 13,613 are in the treated group.

The results are reported in Table 8. In column 1, the dependent variable is *Log loan spread,* and the key independent variable is the interaction term *Treated*After_IPO*. The coefficient on interaction term shows that industry incumbents pay 4.4 percent more interest on bank loans, significant at a 1 percent level. We can see there is no significant difference in loan spread between the treatment group and the control group before IPO even. However after an IPO event, both control and treated firms have higher loan costs, but treated firms pay even higher costs. Column 2 of Table 2 presents the results of difference-in-difference analysis on use of performance pricing provisions. The coef-

TABLE 8. Difference-in-Difference Results

This table presents difference-in-difference regression results on the effect of IPOs on their industry incumbents' bank loan price term. The dependent variable in column 1 is *Log(loan spread)*, which is the natural log of loan spread (AISD), which is the all-in spread drawn defined as the amount the borrower pays in basis points over LIBOR or LIBOR equivalent for each dollar drawn down on the bank loan. The dependent variable in column 2 is *Performance pricing,* which is defined as a dummy variable that equals one if the bank loan includes performance pricing provisions, and zero otherwise. *Treated* is a dummy variable that equals one if the firm is in treated group, otherwise equals zero. *After_IPO* is a dummy variable that equals one if the bank loan is initiated after an IPO event in the industry. *Pre_firm* is an indicator that equals one if the incumbent firms only have bank loans in the pre-IPO period. *Loan size* is the natural logarithm of bank loan amount in millions of dollars. *Secured* is a dummy variable that equals one if the bank loan has a collateral requirement. *Leverage* is total debt (long-term debt plus debt in current liabilities) divided by total assets. *Profitability* is EBITDA divided by the total assets. *Tangibility* is net property, plant, and equipment divided by total assets. *Z-score* equals (1.2 × Working capital + 1.4 × Retained earnings + 3.3 EBIT + 0.999Sales)/Total assets. *Firm size* is defined as the natural logarithm of total assets of the firm. *M/B ratio* is the market value of equity plus book value of debt divided by total assets. *Term spread* is the difference between the yields on 10-year and 2-year Treasury bonds. *Credit spread* is the difference between the yields on BAA and AAA corporate bonds. T-statistics are in parentheses. Significance at 10 percent, 5 percent, and 1 percent level is indicated by *, **, and ***, respectively. In all regressions, standard errors are adjusted for within-firm clustering.

	(1)	(2)
	Log(loan spread)	Performance pricing
Treated	0.2001***	−0.0194
	(0.0251)	(0.1197)
After_IPO	0.1701***	0.1220
	(0.0248)	(0.1322)
After_IPO*Treated	0.3234***	0.2752**
	(0.0260)	(0.1226)
Leverage	0.8473***	0.7618***
	(0.0592)	(0.2463)
Profitability	−0.8190***	2.3959***
	(0.1335)	(0.5721)
Tangibility	−0.1634***	−0.6167**
	(0.0589)	(0.2456)
Z-score	−0.0497***	0.1923***
	(0.0087)	(0.0377)
Firm size	−0.1751***	−0.2139***
	(0.0105)	(0.0414)
M/B ratio	−0.1059***	−0.0226
	(0.0146)	(0.0485)
Loan size	−0.0714***	0.4720***
	(0.0102)	(0.0396)
Log(maturity)	−0.1504***	
	(0.0174)	
Performance pricing	−0.0665***	
	(0.0198)	
Secured		−0.5020***
		(0.1021)
Control for		
Loan types	Yes	Yes
Loan purposes	Yes	Yes
IPO-fixed effects	Yes	Yes
N	9333	7756
Adjusted R^2/McFadden's adjusted R^2	0.548	0.189

ficient of interaction term *Treated*After_IPO* is 0.445, significant at 1 percent level. The result is consistent with our previous analyses.

CONCLUSION

Previous literature focuses on the impact of IPOs on the issuing firms themselves. In this paper, we examine the IPO competitive effects on bank loans from the industry peers' perspectives by investigating how the contract terms change after IPOs in the same industry.

We find that compared to loans initiated before large IPOs in the industry, loans initiated after IPOs have higher loan cost, more employment of performance pricing provisions, and higher commitment fees. We also find that syndicates have fewer lenders and a larger share after IPOs for incumbents. This finding has important implications for investors and creditors, since incumbent firms comprise a disproportionately large part in the post-IPO market capitalization.

In sum, our findings are consistent with the view that issuing firms have a competitive advantage over their industry incumbents. After IPOs, the long-term operating performance of the public incumbents deteriorate, and the information uncertainty of their future performance, as well as information asymmetry, increases. Therefore, competitive effects of IPOs exist and negatively affect industry peers in terms of capital cost. An evaluation for incumbent firms after large IPOs is necessary. Moreover, our results have very important implications for industry peers' product and financing strategies.

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Understanding Convertible Bond Issuances of Chinese Listed Firms

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Abstract

Motivation: This paper investigates why Chinese firms issue convertible bonds.

Premise: Unlike their counterparts in the United States and the European Union, most convertible bonds issued by listed firms in China from 2003 to 2014 are converted to equity before the maturity date. This indicates that the convertible bond in China is used as a backdoor equity financing instrument.

Approach: By using a sample of 77 convertible debt, 655 straight debt, and 1,089 seasoned equity issues in China from 2003 to 2014, we employ a multinomial logit model.

Results: Our regression results show that firms are more likely to issue convertible bonds rather than straight debt when the debt-related cost is low and stock price run-up is high while, compared to seasoned equity issuers, firms issue convertible bonds when the risk-free rate is low.

Conclusion: The overall results suggest that while listed firms in China still seek equity financing first, they issue convertible bonds to take advantage of the interest rate deduction with the assurance to their investors that the convertibles can be converted to equities. In addition, most convertible bonds were underpriced on the offering date, suggesting convertible bond issuers do not exploit the local investors in China.

Consistency: Our understanding on the convertible bond issuance is mainly based on firms in developed markets. Little is known about Chinese firms in this regard. In this paper, we study why firms issue convertible bonds in China by investigating 77 convertible bonds, 655 straight debts, and 1,089 seasoned equities issuances from 2003 through 2014. We find that the average of the *ex*

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post actual conversion rate of convertible bonds is 96.18 percent, indicating that almost all convertible bonds in Chinese stock markets were eventually converted to equities, which is a strong indication that convertibles are used as delayed equity. This motivation is reflected with the equity-like design of most convertible bonds in the Chinese market.

Keywords: capital structure, Chinese bonds, convertible bond issuance, convertible bond underpricing

JEL Classification Codes: G10, G32

INTRODUCTION

Convertible debt has become a major financing source for companies around the world in recent decades (Dutordoir, Strong, and Ziegan 2014). Why companies issue hybrid securities like convertible debt instead of issuing straight debt or equity remains an important question. The related literature has developed theoretical models to explain the convertible debt issuance and to provide empirical evidence concerning whether the theoretical models have explanatory power in the real business world. Different theories explain the use of convertible debt, including the sweetened debt approach (Green 1984; Brennan and Kraus 1987; Brennan and Schwartz 1988; Mayers 1998), the delayed equity approach (Stein 1992), the tax advantage approach (Jalan and Barone-Adesi 1995), the managerial entrenchment approach (Isagawa 2002), and the rationing in the equity markets approach (Lewis, Rogalski, and Seward 2001). Meanwhile, studies suggest that convertible debt issuance is also affected by firm- and country-level corporate governance characteristics (Dutordoir, Strong, and Ziegan 2014) and by investors' demand (Brown et al. 2012; De Jong, Duca, and Dutordoir 2013).

Despite the efforts from the existing literature—which are mainly based on well-developed markets with high institutional similarities (Kang and Stulz 1996; Magennis, Watts, and Wright 1998; Abhyankar and Dunning 1999; Lewis, Rogalski, and Seward 2003; Loncarski, Horst, and Veld 2008; Dutordoir and Van de Gucht 2009)—less is known regarding the motivations for convertibles' issuance in other environments. This paper intends to fill this gap by investigating the determinants that drive the issuance of convertible debts in the world's largest developing economy, the Chinese market.

The Chinese convertible bond market is relatively small in size compared to its Western counterparts. In 2013, the total number of completed deals for convertible bonds in China's domestic market was valued at 14.6 billion USD, which only accounts for around 13 percent of the global market.[1] Nevertheless, because the convertible bond market in China provides a unique institutional and economic environment, it is worth investigating for the following reasons. First, China's bond market has grown rapidly in recent years and, according to the International Monetary Fund, is now ranked as the third largest market in the world following the United States and Japan. The convertible bond market is no exception: according to Zhang, Kan, and Xiao (2017), as of November 7,

[1]See *Financial Times,* January 7, 2014.

2017, 120 Chinese listed firms have announced plans to issue convertible bonds, involving 290 billion RMB (43.6 billion USD). Although there are quite a few studies that advance our understanding regarding the resettable feature of Chinese convertible bonds (Qiu and Zhang 2013; Martin, Qiu, and Zhang 2015), it remains unclear what are the characteristics of the firms that issued convertible bonds. We attempt to fill this void in the literature.

Second, previous studies that focus on Chinese firms' financing selections did not take into consideration the convertible bonds (Chen 2004; Zou and Xiao 2006). Particularly, Chen (2004) argues that due to the lack of proper corporate governance and enforcement of China's Company Law, individual shareholders are not properly protected, and share capital has become a somewhat "free" source of finance.[2] Meanwhile, banks are generally unwilling to lend to small- or medium-sized non-state-owned enterprises (non-SOEs). Thus, a new pecking order may have emerged in which firms prefer equity rather than debt in external financing. Despite the implementation of bankruptcy law in 2006, creditor protection is relatively weak in China (Allen, Qian, and Qian 2005). Bankruptcies are extremely rare since both local and national governments will bail firms out, particularly large firms and state-owned-enterprises (SOEs), to prevent them from failing. One explanation could be that the government relies on those firms to maintain employment levels and to maintain social stability (see, for example, Bai et al. 2000). Such an implicit government guarantee explains the Chinese banks' preference for providing loans to large firms as well as SOEs (Jiang and Kim 2014). Since convertible bonds have both debt and equity features, it is therefore important to test the sequential financing order with the inclusion of the convertible financing option in the Chinese market.

Finally, a strand of literature documents evidence of mispricing in the Chinese warrant market (Xiong and Yu 2011; Powers and Xiao 2013; Liu, Zhang, and Zhao 2014). The warrant-like conversion feature embedded in the local convertible bonds is also likely to be mispriced to take advantage of the "casino-like" markets which are flooded with retail investors.[3] This naturally raises concerns regarding the motivation behind Chinese firms' issuance of convertible bonds and the sophistication of the market.

This paper examines a dataset including 655 straight debt issues, 77 convertible debt issues, and 1,089 equity issues announced from nonfinancial public firms in the Chinese market between 2003 and 2014. Following Erel et al. (2012), we use the multinomial logistic regressions to analyze firms' security choices. Our framework controls for a range of firm-level data as well as security market conditions. We also control for provincial-level data to proxy for investor protection rights. In addition, we analyze the determinants of convertible bond first-day theoretical pricing by using a range of convertible bond characteristics.

Our findings suggest that, first, Chinese companies use convertible debt mainly as a backdoor equity financing instrument, not as sweetened debt. This is consistent with the equity design of most of China's convertible offerings. Spe-

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[2]Chinese firms do not typically pay regular cash dividends, but prefer stock dividends. Allen, Qian, and Qian (2005) observed that Chinese firms tend to underpay cash dividends to their shareholders, compared with firms in other countries. In a recent study, Jiang and Kim (2015) also confirm this finding.

[3]The "casino theory" of China's stock market was first proposed by a Chinese economist Wu Jinglian in 2001. More recently, *The Economist* (2015) dubbed China's stock market "a crazy casino."

cifically, the median (mean) of the *theoretical* conversion probability (the delta) of the convertibles is 41.8 percent (43.8 percent).[4] However, the median (mean) of the ex-post *actual* conversion ratio is 99.80 percent (96.18 percent), which suggests that almost *all* the convertible bonds issued in our sample period were converted to equities before their maturity.

Second, our findings also suggest that firm-level characteristics, ownership concentration, and security market conditions have a significant impact on firms' convertible debt choices over other financial instruments, but the influence from the provincial level of investor protection is insignificant. Interestingly, we find that firms tend to issue convertible bonds rather than straight debts although the debt-related cost is low and the stock price run-up is high. Further, bigger firms tend to issue convertible bonds over seasoned equities when the risk-free rate is low. These findings indicate that Chinese listed firms still prefer equity for external financing (Chen 2004). Firms issue convertible bonds to gain profits from the interest rate reductions and avoid losses from shareholders' wealth through seasoned equities offering. As Liu et al. (2016) find, the market is favorable toward the announcements of convertible bond issuance in China, but unfavorable to seasoned equity offering announcements.

Third, we find that most of the convertible debts were underpriced on the offer date. This implies that the issuances of convertible bonds are not necessary to harm the interests of local investors. In addition, the credit rating of the convertible bond is quite high in our sample, but it does not relate to convertible bond underpricing.

The paper proceeds as follows. The next section reviews the related literature. "Literature Review" provides information on the Chinese convertible debt. "Data" presents the data, and the results of our regression analysis are reported in "Empirical Results," followed by the conclusion.

THE DEVELOPMENT OF THE CONVERTIBLE BOND MARKET IN CHINA

The first convertible bond issued by Chinese listed firms was from Shen Bao An (000009.SZ). At the end of 1992, Shen Bao An issued 500 million RMB convertible bonds in the Shenzhen Stock Exchange. During that time, however, there were no official regulations regarding the convertible bond issuance. The convertible bond issued by Shen Bao An eventually failed to convert to equities due to bad timing and a high conversion price. In 1994, the implementation of the Company Law[5] stipulated the legal status of the convertible bonds, the conditions of the issuance, and the basic rights of the related parties. In 1997, "Interim Measures for the Administration of Convertible Bonds"[6] was approved by the State Council: at that time, only state-owned enterprises (SOEs) were able to issue convertible bonds. The

[4]The delta measure is calculated as $\Delta = e^{-\delta T} N(d_1) = e^{-\delta T} N\left(\frac{1n\left(\frac{s}{x}\right) + \left(r - \delta + \frac{T\sigma^2}{2}\right)}{\sigma\sqrt{T}}\right)$, where δ is the continuously compounded dividend yield for the fiscal year end preceding the announcement date, T is the initial convertible debt maturity (in years), S is the price of the underlying stock measured seven days before the announcement date, X is the conversion price, r is the three month Shanghai interbank offered rate (SHIBOR) (measured on the announcement date), and σ is the annual stock return volatility.

[5]http://www.npc.gov.cn/wxzl/gongbao/2000–12/05/content_5004608.htm

[6]http://www.csrc.gov.cn/pub/shenzhen/xxfw/tzzsyd/ssgs/ssgsrz/ssrzfz/200902/t20090226_95614.htm

interim measures introduced in 1997 set out the provisions for convertible bond issuance, transaction, conversion, and redemption. In April 2001, the Chinese Securities Regulatory Commission (CSRC) issued "Measures for the Issuance of Convertible Bonds by Listed Companies";[7] this document removed the restrictions on non-SOEs to issue convertible bonds and formed the prelude for convertible bond issuance. However, due to the doldrums of the warrant markets, the issuance of convertibles was prohibited from the second half of 2004 until 2005.

On May 6, 2006, the CSRC issued "Measures for the Administration of Securities Issuance of Listed Companies,"[8] and at the same time abolished the previous "Measures for the Issuance of Convertible Bonds by Listed Companies." Some notable requirements that a company that wishes to issue publicly convertible bonds shall comply with are as follows: (1) net assets should be no less than 30 million RMB for a joint stock company, and 60 million RMB for a limited liability company; (2) the average distributable profits in the last three years should be sufficient to cover one year's interests for the bonds; (3) the firm must have maintained a record of positive profitability with a ROE of no less than 6 percent for three consecutive years; (4) the balance of the accumulated corporate bonds after the issuance shall not exceed 40 percent of the net assets at the end of last period; (5) the issuer must have guarantors with joint liabilities or an asset-backed pledge, except for those companies whose audited net assets are no less than 1.5 billion RMB; and (6) net assets should be no less than RMB 1.5 billion if the firm is to issue detachable convertible bonds.

In addition, there are also some restrictions on convertible bond issuance. For example, the convertible bonds must be rated initially at the time of issue and thereafter annually by a qualified credit rating agency; the face value of convertible bond must be 100 RMB; and the minimum period of the convertible bond is one year while the maximum is six years. Although the CSRC did not specific the clauses on call-and-put provisions, these provisions in our sample are quite similar. Under the call provision, the issuer can repurchase the convertible bonds which are not converted if the price of the stock exceeds (usually) 30 percent of the strike price consecutively (15 to 20 days) over a certain period (20 to 30 days); and if the callable price does not usually exceed 105 percent of the par value (100 RMB). In addition, if the remaining value of the convertible is less than 30 million RMB, the issuer can also purchase back all the convertible bonds outstanding. Under the put provision, the investors can sell back the convertibles to the issuer if the price of the stock is lower than 70 percent of the strike price consecutively (20 or 30 days) over a certain period (20 or 30 days), and the puttable price usually does not exceed 105 percent of the par value. Note that in our sample, it is quite rare that the convertible bond triggers the put provision.

LITERATURE REVIEW

Theoretical Rationales for Convertible Bond Issuance Decisions

As shown in the introduction, there are several schools of theories on the motives of convertible bond issuance, among which two main theories stem from *agency cost* and *information asymmetry*, respectively. Several papers argue

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[7]http://www.csrc.gov.cn/pub/zjhpublic/zjh/200804/t20080418_14472.htm

[8]http://www.csrc.gov.cn/pub/hebei/xxfw/gfxwj/200805/t20080503_68707.htm

that convertible debts can reduce a variety of agency costs. It is well known that maximizing the value of the equity and maximizing the value of the firm can, with outstanding risky debt, lead to agency problems. The risk-shifting model of Green (1984) focusses on potential shareholder–debtholder conflicts of interest, arguing that a convertible bond can help mitigate shareholders' incentives to engage in risky, negative net present value (NPV) projects. By adding a conversion option to their bond issues, firms allow debtholders to benefit from the upside potential of their stocks. Convertibles thus reduce the value of the shareholders' residual claim, thereby alleviating the shareholders' tendencies to engage in more risky projects. However, Green's argument is based on the agency problem between management and shareholders. Mayers (1998) complements Green's theory to some extent and considers convertibles as a tool to reduce agency problems between management and shareholders where the company has a sequence of investment opportunities. His sequential-financing model demonstrates that convertible debt is more suitable than either short- or long-term bonds for financing a sequence of investment options of uncertain value. On one hand, compared to long-term bonds, the convertible can economize on issue costs because conversion leaves funds in the firm when the investment turns out to be valuable. On the other hand, compared to short-term bonds, the convertible can control the overinvestment problem by returning funds to debtholders through redemption if the investment turns out to be worthless. Note that a critical assumption in Mayers' model is that convertibles are callable, whereby companies are able to force conversion of the convertible debt into equity when the stock price reaches a threshold for a certain period (investment has a positive value).

A stream of literature also models convertible debts as a device to reduce adverse selection costs resulting from asymmetric information between a firm's insiders and outsiders. Brennan and Kraus (1987) and Brennan and Schwartz (1988) develop a model that explains a firm's choice of financing instruments when investors and management disagree on the riskiness of a company. In this case, high perceived levels of risk result in the firm having to pay a higher interest rate on straight debt than managers find reasonable. This problem can be mitigated by issuing convertible bonds. Because the cost of convertibles is evaluated on a weighted basis of the debt component and the equity option component, higher perceived risk translates into lower value of the straight debt component; but at the same time it increases the value of the equity option component, resulting in a reasonably priced convertible debt. A second group of adverse selection models builds on the assumption of asymmetric information about firm value rather than about firm risk. Stein (1992) suggests that firms issue convertible bonds to acquire equity through the "backdoor" in situations where informational asymmetries render conventional equity issues unattractive due to high issue costs and dilution (Myers and Majluf 1984). The intuition for the role of convertible debt as "backdoor" equity financing rests on the trade-off between the sale of mispriced corporate securities and the costs of financial distress. Convertible bonds attenuate the high expected costs of financial distress associated with a debt issue and reduce the large negative announcement effects that typically occur with common equity issues.

Empirical Evidence on Convertible Debt Issuer Motivation

Previous empirical literature on convertible debt issuance motives mainly relies on qualitative survey-based analysis and quantitative analysis.[9] Early U.S. survey results obtained by Billingsley and Smith (1996) and Graham and Harvey (2001) are consistent with both the *sweetened debt* and the *delayed equity* viewpoints. However, in a more recent survey analysis, Dong, Dutordoir, and Veld (2017) report evidence to support information asymmetry between management and investors, although it is to be noted that their sample firms are from English-speaking countries (Australia, Canada, the United Kingdom, and the United States). Bancel and Mittoo (2004a, 2004b) focus on the motivations behind Western European convertible debt offerings. Bancel and Mittoo (2004a) survey managers whose firms have already issued convertible debt and obtain support for both viewpoints. Bancel and Mittoo (2004b) further survey companies that have seriously considered issuing convertible debt over the previous ten years; their findings are mainly consistent with Stein's delayed equity perception.

For quantitative analysis, Lewis, Rogalski, and Seward (1999) suggest that both the sweetened debt and delayed equity financing viewpoints are valid in their results by using a sample of 203 convertible issues on the U.S. market between 1977 and 1984. They point out that firms that issue debt-like convertibles are likely to control for the risk-shifting problem and firms that issue equity-like convertibles try to mitigate information asymmetry problems. Dutordoir and Van de Gucht (2009) replicate the approach of Lewis, Rogalski, and Seward (1999) in a Western European setting and find that European convertibles mainly serve as sweetened debts.

DATA

Security Issues

We collect all convertible debt, straight debt, and seasoned equity issues conducted by domestic firms listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange from 2003 to 2014. The seasoned issue data are downloaded from Seasoned Equity Offerings Database and China's Bond Market Database. We obtain firm-level financial data from the RESSET database and the Wind database. To avoid survival bias, we include all firms that have been delisted from the stock exchanges. We exclude any firm with a seasoned offering that does not have a CSRC report of the filing in line with Liu et al. (2016); we remove issues of different security types made by the same firm during the same fiscal year in line with Hovakimian, Opler, and Titman (2001); we also remove financial firms (Chinese Securities Regulatory Commission industry code J) because they operate in a stringent regulatory environment and follow different accounting standards. After the screening process, we are left with a final sample of 77 convertible debt, 655 straight debt, and 1,089 seasoned equity issues. Note that these figures are comparable with Liu et al. (2016) who investigate similar data in China between 1991 and 2010. The high proportion of equity issues in our sample contrast with the number of seasoned issues in Western European

[9]See Loncarski, Horst, and Veld (2008) and Dutordoir, Strong, and Ziegan (2014) for an extensive overview of empirical evidence regarding convertible debt issuance motivations.

countries (Dutordoir and Van de Gucht 2009), of which more than half of the issues were straight bonds.

Table 1 presents the samples sorted by issue year. We find that there are substantial temporal fluctuations in equity and convertible debt offering volumes. As we mentioned in the previous section, convertible bond issue was paused in 2005 due to the market downturn. The number of the debt issues was relatively stable—it increased steadily prior to 2012, but reduced significantly thereafter. The volume of seasoned equity issuance first peaked in 2007 before the financial crisis, then dropped, but recently recovered. It seems that the equity market and debt market complement each other.

Variable Description

To facilitate comparisons with the determinants of firms that issue convertible bonds over straight debt and seasoned equity, in our choice of independent variables we closely follow prior literature. Essentially, the selected variables belong to one of three categories: (1) firm-level characteristics, (2) ownership concentration and political linkage, and (3) macroeconomic variables and investor protection proxies at provincial levels. Following Dutordoir and Van de Gucht (2009), the first group of variables includes:

1. *Total assets:* book value of total assets of the firms. Logged for all regressions. Total assets can proxy for the magnitude of asymmetric information and financial distress costs (Lewis, Rogalski, and Seward 1999).
2. *Market-to-book:* market-to-book ratio, the market capitalization divided by the book value of total assets, both measured at the end of the calendar year prior to the yearly observation. We calculate market capitalization as the closing share price, multiplied by total shares outstanding. It is logged

TABLE 1. Descriptive Statistics for Security Issues

This table reports the number of issues by year, along with percentages, for a sample of convertible bonds, straight debt, and seasoned equity issues offered by Chinese listed firms (excluding financials) between January 2003 and December 2014.

	Convertible Issuance		Debt Issuance		Equity Issuance	
Year	Number of Issues	Percentage	Number of Issues	Percentage	Number of Issues	Percentage
2003	14	18.18	0	0	13	1.19
2004	11	14.29	2	0.31	11	1.01
2005	0	0	19	2.9	4	0.37
2006	6	7.79	55	8.4	50	4.59
2007	9	11.69	28	4.27	143	13.13
2008	4	5.19	25	3.82	95	8.72
2009	5	6.49	48	7.33	89	8.17
2010	3	3.9	56	8.55	113	10.38
2011	5	6.49	108	16.49	118	10.84
2012	3	3.9	155	23.66	84	7.71
2013	7	9.09	95	14.5	159	14.6
2014	10	12.99	64	9.77	210	19.28
Total	77	100	655	100	1,089	100

for regression. The MB ratio is a common proxy of future growth opportunities; firms that have higher growth opportunities usually have lower cost of capital.

3. *Sales growth:* growth in sales in the fiscal year before the security issue.
   The *total assets, market-to-book,* and *sales growth* measures can proxy for a firm's general financing costs.
4. *Leverage:* total debt divided by total assets.
5. *ROA:* return on assets, calculated as net income divided by the book value of total assets. A high profitability before the security issue allows a firm to easily pay the interest on its debt.
6. *Tax/TA:* the ratio of income taxes to total assets.
7. *Volatility:* stock return volatility, annualized stock return volatility based on daily stock returns measured over the 60 days before the security issue. It is logged for all regressions.
   The *leverage, ROA, tax/TA,* and *volatility* measures can proxy for a firm's debt-related financing costs.
8. *Stock run-up 1:* cumulative daily stock return over the window 90 to 2 trading days before the security issue. Stockholders may interpret the run-up as a signal of good investment projects.
9. *Stock run-up 2:* cumulative daily stock return over the window 360 to 91 trading days before the security issue.
10. *Slack/TA:* financial slack to total assets, calculated as net operating cash flow minus cash dividends minus capital expenditures over the book value of total assets.
11. *Issue size/MV:* offering proceeds to market capitalization.

The last four measures above can proxy for the firm's equity-related financing costs. Both *slack/TA* and *issue size/MV* are positively correlated with equity-related financing costs.

The second category includes variables that are set to capture ownership concentration and political linkages:

1. *Herfindal 5:* an indicator for ownership concentration, calculated as the sum of squared ownership proportions held by each of the top five shareholders.
2. *State ownership:* captures the proportion of state-held shares at the end of year.

These two variables are important in a Chinese setting because there usually exists a large shareholder in listed firms and ownership is quite concentrated. Further, the presence of the state ownership can offer implicit loan guarantees and lower the cost of firms' financial distress (Chang, Chen, and Liao 2014).

The third group category includes macroeconomic variables and provincial investor protection levels. The variables are:

1. *Market run-up:* Return on the Shanghai Composite index over the window (–90, –2).

2. *Market volatility:* annualized Shanghai Composite index return volatility based on daily index returns measured over the 60 days before the security issue.
3. *Risk-free rate:* before 2007, three-month coupon rate for the People's Bank of China (PBOC) notes; after 2007, three-month Shanghai Interbank Offered Rate (Shibor).
4. *Pprts:* property rights is the number of domestic trademark applications per firm for a certain province and year.
5. *Rlaw:* rule of law is the number of lawyers per 10,000 people for a certain province and year.

Pprts and *Rlaw* can be used to proxy for legal protection on a provincial level (Hasan, Song, and Wachtel 2014) in China because, similar to Korkeamaki's (2005) hypothesis, presumably, investors in regions with weaker creditor (shareholder) protection rights prefer security types with a smaller debt (equity) component size, which in turn affects the firm's security design.

For the sake of brevity, only the mean and median values of variables of each security issue type are reported in panel A of Table 2. The mean (median) value of total assets for firms that issue convertible bonds in our sample is 13,500 (4,250) million RMB, which is much smaller than convertible debt issuers examined in a EU-based study (Dutordoir and Gucht 2009), but larger than the sample by De Jong, Duca, and Dutordoir (2013) of U.S. firms issuing convertible bonds from 1992 to 2007. Another interesting feature is that the biggest average size is found for firms that issued straight debts in both Dutordoir and Gucht's (2009) and De Jong, Duca, and Dutordoir's (2013) samples, but in our sample, the average size of firms that issue convertible bonds and straight debts is similar. The mean (median) leverage for convertible bond issuers in our sample is generally higher than their counterparts in the United States and the European Union.

We are also interested in the first-day-underpricing of convertible bonds. The underpricing is calculated as the theoretical price of convertible bond minus the face value of the convertible bond. Like Chan and Chen (2007) and Ammann, Kind, and Wilde (2003), we use the famous Tsiveriotis and Fernandes (1998) model to obtain the theoretical price of the convertible bonds. Following Chan and Chen (2007) and Datta, Iskandar-Datta, and Patel (1997), we investigate the determinants of convertible bond underpricing by collecting the following variables:

1. *Issue volume:* the total issue volume of convertible bonds.
2. *Credit rating:* as per requested by the CSRC, convertible bond issuers shall obtain an initial rating from the one of the rating agencies[10] in China. The initial ratings of Chinese convertible bonds in our sample are all above A–. In total there are five different ratings, ranging from AA– to AAA. We assign each a numerical ranking, from highest (5) to lowest (1), AAA = 5, AAA– = 4, AA+ = 3, AA = 2, and AA– = 1.
3. *Coupon rate:* coupon rate on convertible bond face value. Note that some convertible bonds have different coupon rates for each year; in those cases, we use the average of the coupon rate.

[10]The three major rating agency firms in China are United Credit Ratings, China Cheng Xin International Credit Rating, and Dagong Global Credit Rating.

TABLE 2. Summary Statistics

Panel A reports descriptive firm-specific statistics for samples of straight debt, convertible debt, and equity offerings made by Chinese industrial companies between January 2003 and December 2014. The security samples are retrieved from the Seasoned Equity Offerings Database and China's Bond Market Database. The convertible debt sample consists of 77 offerings, the straight debt sample consists of 655 offerings, and the equity sample consists of 1,089 offerings. Firm-specific characteristics are obtained from RESSET and Wind databases and measured at fiscal year-end prior to the security announcement date, unless otherwise indicated. Panel B reports descriptive convertible-specific statistics for samples of 77 convertible debt offerings made by Chinese industrial companies between January 2003 and December 2014. Variable descriptions can be found in Table A1.

	Convertible Issuance		Debt Issuance		Equity Issuance	
Panel A	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Firm-Specific Variables						
Total assets (million RMB)	13,500	4,250	12,400	5,790	7,320	2,820
Volatility	0.052	0.046	0.062	0.055	0.060	0.055
Stock run-up1	0.036	0.035	0.005	−0.002	0.026	0.013
Stock run-up2	0.032	0.010	−0.022	−0.035	0.095	0.081
Leverage	0.352	0.434	0.524	0.539	0.474	0.477
Profitability (ROA)	0.029	0.020	0.020	0.012	0.027	0.017
Market-to-book	0.601	1.017	0.780	0.968	1.059	1.512
Slack/TA	−0.087	−0.003	0.017	−0.009	−0.006	−0.010
Tax/TA	0.021	0.012	0.010	0.008	0.014	0.009
Issue size/MV	0.206	0.166	0.106	0.083	0.201	0.163
Sales growth	0.162	0.095	0.132	0.076	0.166	0.121
State ownership	0.227	0.0002	0.125	0	0.122	0
Herfindal 5	0.262	0.243	0.189	0.163	0.175	0.144
Macroeconomic- and Provincial-Level Variables						
Market run-up	0.033	0.029	0.030	0.029	0.033	0.021
Market volatility	0.014	0.013	0.013	0.012	0.014	0.013
Risk-free rate	0.033	0.025	0.043	0.039	0.038	0.043
Pprts	4.181	0.407	4.575	0.57	3.105	0.57
Rlaw	0.774	0.479	0.751	0.609	0.808	0.609
Panel B	**Mean**	**Median**	**S.D.**	**Min.**	**Max.**	
Underpricing1	9.371	7.994	9.751	−9.738	41.077	
Underpricing2	9.432	8.152	9.829	−9.737	41.909	
Credit rating	3.558	4	1.482	1	5	
Issue volume (million)	13.6	8.2	15.6	2	100	
Coupon rate (%)	1.089	1.1	0.448	0.5	2.2	

Panel B of Table 2 reports the statistics. Both underpricing measures are calculated as theoretical convertible price by Tsiveriotis and Fernandes's (1998) model minus the convertible bond face value (100 RMB). *Underpricing1* is calculated by assuming stock price follows a trinomial tree in Tsiveriotis and Fernandes's (1998) model while *underpricing2* assumes that stock price follows a binomial tree. Both underpricing measures are similar, the mean (median) is 9.371 (7.994) of underpricing, which suggests that convertible bonds are underpriced on the initial offering day.[11] The mean (median) of credit rating is 3.558

[11]We also use the Black-Scholes model to calculate the underpricing of convertible bond and obtain a very similar result with a mean (median) of 10.591 (9.840).

(4) which indicates that the convertibles are among the bonds with highest ratings; these contrasts sharply with the U.S. sample in Chan and Chen (2007). The issue volume of convertible bond ranges from 2 million to 100 million with a mean (median) of 13.6 (8.2) million. The average coupon rate is about 2 percent lower than the risk-free rate; this strongly indicates the equity feature of convertible bond issued in China.

Difference-in-Mean Test

Table 3 reports *t*-statistics for pairwise differences in means between the convertible sample and the other two security samples. Most of the significant differences between the two groups are found in firm-specific characteristics, suggesting that convertible bond issuers have different firm-specific characteristics than the other two groups, but no major difference is found in macroeconomic- and provincial-level variables except for the risk-free rate, indicating that firms tend to issue convertible bonds when the risk-free rate is relatively low. Specifically, compared to straight debt issuers, convertible bond issuers have a significantly smaller stock return volatility, leverage, and market-to-book ratio, and a significantly higher stock run-up, ROA, tax, issue size, state ownership, and ownership concentration. In addition, convertible issuers differ significantly from equity

TABLE 3. Pairwise Difference-in-Mean Test

This table reports pairwise difference-in-mean tests of firm characteristics between convertible bond (CB) and straight debt and convertible bond (CB) and seasoned equity-issuing firms. Table A1 gives the definitions of all the variables. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

	CB versus Straight Debt	CB versus Equity
Firm-Specific Variables		
Total assets (million RMB)	1,110	6,170***
Volatility	−0.010**	−0.008**
Stock run-up1	0.031**	−0.004
Stock run-up2	0.054**	−0.074*
Leverage	−0.172***	−0.122***
Profitability (ROA)	0.008**	0.002
Market-to-book	−0.179***	−0.458***
Slack/TA	−0.104	−0.081
Tax/TA	0.011***	0.007***
Issue size/MV	0.117***	0.005
Sales growth	0.081	−0.004
State ownership	0.101***	0.104***
Herfindal 5	0.072***	0.087***
Macroeconomic- and Provincial-Level Variables		
Market run-up	0.003	−0.0005
Market volatility	0.001*	−0.0003
Risk-free rate	−0.006***	−0.005***
Pprts	−0.393	1.077
Rlaw	0.022	−0.035

issuers on many dimensions: they have larger size, tax, state ownership, and ownership concentration, but they are smaller in stock return volatility, leverage, and market-to-book ratio.

To check for multicollinearity problems, we analyze pairwise Pearson correlations between the variables, and present the correlation table in the appendix. The results of this analysis indicate that correlations do not exceed 0.53 and are below 0.3 for the majority of variables.

EMPIRICAL RESULTS

Model Selection

The descriptive statistics and the univariate comparisons in the previous section both suggest that firm characteristics and macroeconomic conditions can affect the ways in which firms raise convertible debts. To identify the effects on the issuance of the firms' funding choices, it is important to estimate this relation in a multivariate setting. Consequently, we employ discrete-choice models that estimate the likelihood of a firm issuing a specified type of security. When a listed firm needs to obtain public financing, it can issue a straight bond, convertible bond, or seasoned equity. Given the number of potential alternative outcomes, we utilize econometric approaches that allow for multiple discrete choices.

We select the multinomial logit model[12] because it estimates a system in which independent variables affect the choice among a finite number of alternative outcomes. This model is used to predict the probabilities of categorically dependent variable, which has *two or more* possible outcome classes. Whereas the logistic regression model is used when the dependent categorical variable has only two outcome categories.

The output of the multinomial logit model consists of two pairwise regressions: one that models firms' likelihood to choose convertible bonds over straight debts (set as the base outcome) and one that models firms' likelihood to choose convertibles over seasoned equity (set as the base outcome). Specifically, we estimate the following model:

$$\Pr(security\ type = j) = \frac{e^{\beta_j' x}}{\sum_1^3 e^{\beta_k' x}} \tag{1}$$

where j equals 1 if the firm issues convertible bonds, 2 for straight debts, and 3 for seasoned equity offerings. Note that these pairwise regression results are the outcome of the model that simultaneously incorporates all three security types, i.e., 77 convertible bonds, 655 straight debts, and 1,089 seasoned equity offerings.

The Choice between Convertible Bond and Straight Debt

Table 4 reports the results of the multinomial logit analysis of the determinants of firms' choice between convertible debt and straight debt. The results in regression M(1) are largely consistent with the univariate results. In particular, convertible debt issuers have a significantly larger size, stock price run-up,

[12]A Hausman test is applied before the multinomial logit model to rule out the possibility of the assumption that the independence of irrelevant alternatives (IIA) is violated.

TABLE 4. Multinomial Logistic Regression Analysis of the Choice between Convertible and Straight Debt

This table reports the coefficients and *t*-statistics of multinomial logit regressions for the choice between convertible debt and straight debt. These pairwise regression results are the outcome of a multinomial security choice model that simultaneously incorporates the choice between convertible debt, straight debt, and equity. Table A1 gives the definition of all the variables. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Variables	M1	M2	M3
Total assets (logged)	0.263*	0.318**	0.076
	[1.827]	[2.101]	[0.490]
Volatility (logged)	−0.548***	−0.556***	−0.544***
	[−2.910]	[−2.914]	[−2.826]
Stock run-up1	3.404***	3.440***	3.349***
	[2.625]	[2.644]	[2.584]
Stock run-up2	1.866***	1.906***	2.058***
	[2.719]	[2.767]	[2.971]
Leverage	−3.451***	−3.585***	−3.203***
	[−4.619]	[−4.769]	[−4.243]
Profitability (ROA)	6.907	7.008	5.317
	[1.616]	[1.619]	[1.231]
Market-to-book (logged)	0.302	0.283	0.218
	[1.099]	[1.017]	[0.790]
Issue size/MV	11.430***	11.484***	10.907***
	[6.966]	[6.974]	[6.641]
Slack/TA	−0.447*	−0.462*	−0.438*
	[−1.807]	[−1.841]	[−1.788]
Tax/TA	11.214	12.000	10.519
	[1.285]	[1.369]	[1.192]
Sales growth	0.065	0.054	0.087
	[0.168]	[0.140]	[0.226]
Market run-up	−0.916	−0.893	−1.003
	[−0.948]	[−0.913]	[−1.031]
Market volatility	48.272*	46.545*	51.992*
	[1.737]	[1.663]	[1.889]
Risk-free rate	−11.055	−13.372	−7.952
	[−0.890]	[−1.067]	[−0.623]
Pprts		−0.022	
		[−1.570]	
Rlaw		0.058	
		[0.300]	
State ownership			0.170
			[0.278]
Herfindal 5			3.136***
			[2.981]
Constant	−10.376***	−11.449***	−7.039**
	[−3.116]	[−3.329]	[−2.012]
Pseudo R2	0.3034	0.3049	0.3085
Observations	1,821	1,821	1,821

issue proceeds, and stock market volatility, and significantly smaller stock return volatility and leverage than straight debt issuers. Our results contrast sharply with the finding from similar studies in the United States (Lewis, Rogalski, and Seward 1999) and the European Union (Dutordoir and Van de Gucht 2009), in which they find that firms tend to issue convertible bonds when the debt-related cost is higher, and convertible bond issuers are smaller in size than straight debt issuers. Since most of the convertible bonds are finally converted to equities in our sample, our finding provides further evidence on financing behavior of Chinese listed firms: they still prefer equity financing (Chen 2004; Zou and Xiao 2006). That is, instead of directly issuing seasoned equities, firms can choose to issue convertible bonds as a delayed equity financing method. The positive coefficients on stock price run-up and market volatility show that convertible bond issuers have some timing ability; they issue convertibles when stock performs well and the market is more volatile to assure the investors that their convertible bonds could be converted in the future.

M(2) and M(3) report the regression results with provincial-level legal protection proxies and ownership measures. We do not observe significant coefficients on the two legal protection proxies and the state ownership measure. The positive and significant coefficient on the ownership concentration measure (Herfindal 5) indicates that convertible bond issuers have more concentrated ownership. This finding provides some support for Green's (1984) risk-shifting theory, that convertible bonds can be used to alleviate agency conflicts between shareholders and debtholders.

The Choice between Convertible Bond and Seasoned Equity Offering

This section looks at the determinants of firms' propensity to issue convertible debt instead of seasoned equity. Like the previous section, the results from the multinomial logit regression are in line with most of the pairwise differences in mean tests. As can be seen from M(1) in Table 5, compared to seasoned equity issuers, convertible debt issuers have a significantly larger size and tax, and significantly smaller leverage, market-to-book ratio, issue proceeds, and risk-free rate. The results show that most of the equity cost-related measures (stock price run-up, financial slack, and issue proceeds) are not significant; instead it seems that firms issue convertible bonds not due to higher equity-related cost, but because they are large firms that want to take advantage of the low risk-free rate, and tax-shield benefits of debt financing.

The regression results with provincial-level investor protection proxies and ownership measures from M(2) and M(3) are quite similar to the previous section. We only find positive and significant coefficient on ownership concentration. Across all the regressions, pseudo-R^2 is above 30 percent, slightly higher than the corresponding measures recorded by Lewis, Rogalski, and Seward (1999) and Dutordoir and Van de Gucht (2009). This indicates that the choice between convertibles, straight debt, and equity is partially predictable using pre-offering information.

The Determinants of Convertible Bond Underpricing

This section investigates the determinants of convertible bond underpricing. Inspired by the previously mentioned related papers (Datta, Iskandar-Datta, and Patel 1997; Chan and Chen 2007), we include bond credit rating, issue volume, coupon rate, and stock price run-up prior to the issuance as independent variables. We should expect a negative relationship between underpricing and bond credit rating, because bonds with lower ratings tend to underprice more to at-

TABLE 5. Multinomial Logistic Regression Analysis of the Choice between Convertible and Seasoned Equity Offering

This table reports the coefficients and *t*-statistics of multinomial logit regressions for the choice between convertible debt and seasoned equity. These pairwise regression results are the outcome of a multinomial security choice model that simultaneously incorporates the choice between convertible debt, straight debt, and equity. Table A1 gives the definition of all the variables. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Variables	M1	M2	M3
Total assets (logged)	0.422***	0.469***	0.212
	[2.964]	[3.159]	[1.376]
Volatility (logged)	−0.280	−0.288	−0.278
	[−1.562]	[−1.584]	[−1.510]
Stock run-up1	1.443	1.446	1.361
	[1.145]	[1.145]	[1.077]
Stock run-up2	−0.449	−0.435	−0.244
	[−0.682]	[−0.658]	[−0.366]
Leverage	−4.220***	−4.348***	−3.978***
	[−5.895]	[−6.025]	[−5.481]
Profitability (ROA)	3.069	2.961	1.386
	[0.784]	[0.746]	[0.351]
Market-to-book (logged)	−1.342***	−1.349***	−1.445***
	[−5.099]	[−5.062]	[−5.421]
Issue size/MV	−5.690***	−5.627***	−6.331***
	[−3.916]	[−3.862]	[−4.338]
Slack/TA	−0.387	−0.403*	−0.381
	[−1.629]	[−1.668]	[−1.624]
Tax/TA	18.715***	20.013***	17.682***
	[2.889]	[3.039]	[2.686]
Sales growth	−0.263	−0.272	−0.240
	[−0.708]	[−0.734]	[−0.647]
Market run-up	−0.004	0.053	−0.078
	[−0.004]	[0.057]	[−0.084]
Market volatility	−2.442	−3.610	1.054
	[−0.092]	[−0.135]	[0.040]
Risk-free rate	−25.025**	−27.093**	−21.468*
	[−2.072]	[−2.230]	[−1.726]
Pprts		−0.019	
		[−1.404]	
Rlaw		−0.046	
		[−0.245]	
State ownership			0.246
			[0.419]
Herfindal 5			3.604***
			[3.546]
Constant	−9.166***	−10.011***	−5.398
	[−2.810]	[−2.989]	[−1.570]
Pseudo R2	0.3034	0.3049	0.3085
Observations	1,821	1,821	1,821

tract investors (Datta, Iskandar-Datta, and Patel 1997; Chan and Chen 2007). This also applies to coupon rate. We should expect a positive sign from the coefficient on issue volume, as the larger the size of issue proceeds the firm wants to sell to investors, the higher underpricing it should have. Chan and Chen (2007) also find that firms underprice convertible bonds more when they experience a stock price crash prior to the issuance; if this is the case, we should expect a negative sign on coefficients of the stock price run-up measures.

We use both underpricing measures as dependent variables, and we also substitute issue size/MV to issue volume as a robustness check. However, the regression results in Table 6 reveal that only stock price run-up is statistically significant but positive. One possible explanation is that firms whose stock prices perform are more likely to strategically underprice the convertible bonds to attract more investors. The coefficient on credit rate is of the expected sign but insignificant, possibly because the lack of variation in the credit rate measure in our sample.

Discussion of the Results

Overall, the results from Table 4 and Table 5 reveal significant differences between convertible bond issuers and the other two security issuers. Chinese convertible bond issuers tend to be large, mature firms with more debt capacity than the small, high-risk, high-growth firms dominating the U.S. convertible debt-issuer universe. But unlike EU convertible bond issuers that are also found to have similar features, Chinese convertibles are more equity-like—the average theoretical conversion rate (delta measure) is 43.8 percent, which is much

TABLE 6. OLS Regression of the Determinants of Convertible Bond Underpricing

This table reports the coefficients and heteroskedasticity-adjusted robust *t*-statistics of OLS regressions for the determinants of convertible bond underpricing. Table 2 gives the definitions of all the variables. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Expected Sign	M1	M2	M3	M4
Variables		underpricing1	underpricing2	underpricing1	underpricing2
Issue Volume	+	−0.943	−0.990		
(logged)		[−0.676]	[−0.695]		
Issue size/MV	+			−8.719	−9.581
				[−0.941]	[−1.029]
Credit rating	−	−0.302	−0.291	−0.435	−0.425
		[−0.408]	[−0.389]	[−0.590]	[−0.571]
Coupon rate	+	−0.627	−0.509	0.921	1.156
		[−0.280]	[−0.225]	[0.357]	[0.444]
Stock run-up1	−	1.820	1.265	0.857	0.231
		[0.159]	[0.109]	[0.074]	[0.020]
Stock run-up2	−	18.241***	18.500***	16.696***	16.786***
		[3.108]	[3.111]	[2.713]	[2.703]
Constant		25.632	26.276	11.147***	11.115***
		[1.099]	[1.103]	[3.110]	[3.105]
R-squared		0.159	0.160	0.165	0.168
Observations		77	77	77	77

higher than the corresponding figure (27.96 percent) in a sample of Western European companies (Dutordoir and Van de Gucht 2009). So why is this the case? Recall the traditional pecking order theory of Myers (1984) where, when financing is needed, firms shall first rely on internal financing, then debt, and raising equity as a "last resort." However, due to the different institutional environment in China, such as weak creditor protections and ineffective bankruptcy enforcement, dominated state-controlled firms and concentrated ownership, the controlling shareholder and the managers have the incentive to issue seasoned equity when a financing is needed, Chen (2004) thus proposes a new pecking order model in China, i.e., retained funding, equity, and finance.

Our finding is generally consistent with Chen's (2004) argument: we find that firms tend to issue convertible bonds even when the debt-related cost is lower and debt capacity is higher. The question remains, however, as to why Chinese convertible issuers do not tap the seasoned equity market instead. The regression results displayed in Table 5, the low coupon rate, and the unfavorable market reaction to SEOs (Liu et al. 2016) identify a consistent picture to answer this question: convertible bond issuers are larger firms with higher debt capacity, and also want to take advantage of the interest rate deduction and to avoid shareholders' wealth loss.

CONCLUSION

Our understanding on the convertible bond issuance is mainly based on firms in developed markets; little is known about Chinese firms in this regard. This paper studies why firms issue convertible bonds in China by investigating 77 convertible bonds, 655 straight debts, and 1,089 seasoned equities issuances from 2003 to 2014. We find that the average of the *ex post* actual conversion rate of convertible bonds is 96.18 percent, indicating that almost all convertible bonds in Chinese stock markets were eventually converted to equities, which is a strong indication that convertibles are used as delayed equity. This motivation is reflected with the equity-like design of most convertible bonds in the Chinese market. Further, our multinomial logit model shows that firms tend to issue convertible bonds over straight debts when the debt-related cost is low and the stock price run-up is high, and bigger firms tend to issue convertible bonds over seasoned equities when the risk-free rate is low. In addition, we find that the convertible bonds in China are on average underpriced on the initial trading day.

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Appendix

TABLE A1. Variable Description

Variable Name	Variable Definition
Total assets (million RMB)	Total assets denote booking value of total assets.
Volatility	*Volatility* denotes the annualized stock return volatility, and is based on daily stock returns measured over the 60 days before the security issue.
Stock run-up1	*Stock run-up1* is the cumulative daily stock return over the window 90 to 2 trading days before the security issue.
Stock run-up2	*Stock run-up2* is the cumulative daily stock return over the window 360 to 91 trading days before the security issue.
Leverage	*Leverage* is total debt divided by total assets.
Profitability (ROA)	*Profitability* is return on assets, calculated as net income divided by the book value of total assets.
Market-to-book	*Market-to-book* is the market capitalization divided by the book value of total assets.
Slack/TA	*Slack/TA* denotes financial slack to total assets, calculated as net operating cash flow minus cash dividends minus capital expenditures over the book value of total assets.
Tax/TA	*Tax/TA* is the ratio of income taxes to total assets.
Issue size/MV	*Issue size/MV* is offering proceeds to market volume (capitalization).
Sales growth	*Sales growth* is yearly sales growth.
State ownership	*State ownership* captures the proportion of state-held shares at the end of year.
Herfindal 5	*Herfindal 5* is an indicator for ownership concentration, calculated as the sum of squared ownership proportions held by each of the top five shareholders.
Market run-up	*Market run-up* is calculated as return on the Shanghai Composite index over the window (–90 days, –2 days) before the security issue.
Market volatility	*Market volatility* is the annualized Shanghai Composite index return volatility based on daily index returns measured over the 60 days before the security issue.
Risk-free rate	*Risk-free rate* before 2007 is three-month coupon rate for People's Bank of China (PBOC) notes; after 2007, it is three-month Shibor (Shanghai interbank offered rate).
Pprts	*Pprts* is property rights; it denotes the number of domestic trademark applications per firm for a certain province and year.
Rlaw	*Rlaw* is rule of law; it denotes the number of lawyers per 10,000 people for a certain province and year.
Underpricing1	*Underpricing1* is convertible bond underpricing which is calculated by assuming that stock price follows a trinomial tree in the model by Tsiveriotis and Fernandes (1998).
Underpricing2	*Underpricing2* is convertible bond underpricing which is calculated by assuming that stock price follows a binomial tree in the model by Tsiveriotis and Fernandes (1998).
Credit rating	*Credit rating* is convertible bond credit rating: in total there are five different ratings, ranging from AA– to AAA. We assign each a numerical ranking, from highest (5) to lowest (1), AAA = 5, AAA– = 4, AA+ = 3, AA = 2, and AA– = 1.
Issue volume (millions)	*Issue volume* is the total issue volume of convertible bond.
Coupon rate (%)	*Coupon rate* denotes the interest rate on convertible bond face value. Note that some convertible bonds have different coupon rates for each year; in those cases, we use the average of the coupon rate.

TABLE A2. Correlation Matrix

Note: This table presents Spearman pairwise correlation coefficients among variables based on the full sample that includes 1,821 firm-year observations. Bold text indicates that the coefficient is significant at 5 percent or higher significance level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Total assets	1													
(2) Volatility	**0.092**	1												
(3) Stock run-up1	−0.039	**0.08**	1											
(4) Stock run-up2	**−0.082**	0.044	**0.122**	1										
(5) Leverage	**0.388**	**0.178**	**0.081**	0.046	1									
(6) Profitability	0.043	**0.086**	−0.043	**0.166**	**−0.179**	1								
(7) Market-to-book	**−0.537**	**−0.08**	**0.063**	**0.261**	**−0.458**	**0.313**	1							
(8) Slack/TA	**−0.157**	0.039	0.007	−0.013	**0.048**	**−0.141**	**−0.302**	1						
(9) Tax/TA	0.028	0.031	**0.077**	−0.017	**0.066**	−0.027	0.002	0.001	1					
(10) Issue size/MV	**−0.203**	**−0.077**	0.024	**0.051**	**−0.211**	**0.163**	**0.248**	**0.209**	0.057	1				
(11) Sales growth	**−0.039**	−0.011	**0.048**	**0.058**	**−0.057**	**0.103**	0.028	−0.021	0.032	0.004	1			
(12) Market run-up	0.007	**0.053**	**0.347**	0.288	**0.046**	0.028	**0.06**	−0.044	0.019	0.046	0.041	1		
(13) Market volatility	**0.082**	**0.28**	0.033	0.175	**0.155**	**0.163**	−0.021	0.032	−0.008	**−0.061**	0.005	0.035	1	
(14) Risk-free rate	**−0.079**	**−0.256**	**−0.24**	−0.115	−0.064	−0.16	**0.111**	**−0.088**	0.007	**−0.048**	**−0.071**	**−0.299**	**−0.361**	1

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