Three essays on finance

Xia, Chongwu

2016

Xia, C. (2016). Three essays on finance. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/69239>

<https://doi.org/10.32657/10356/69239>

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

THREE ESSAYS ON FINANCE

XIA CHONGWU

NANYANG BUSINESS SCHOOL

2016

THREE ESSAYS ON FINANCE

XIA CHONGWU

NANYANG BUSINESS SCHOOL

A thesis submitted to Nanyang Technological University

in partial fulfilment of the requirement for the degree of

Doctor of Philosophy

2016

Acknowledgements

First and foremost, I would like to thank my supervisor Prof Luo Jiang, for his deep understanding and immense knowledge on finance, as well as his great patience and enthusiasm. Without Prof Luo's invaluable guidance and continuous help, this thesis would be impossible. His influence goes beyond to setting a great example for my future career in academy. My deep gratitude also goes to the other committee members: Prof Chen Zhanhui and Prof Feng Qu. I received tremendous help from them, particularly on technical skills. They were patient enough to even answer my detailed questions.

I would like to thank Prof Chen Tao and Prof Zhang Lei as well. They also provided invaluable guidance and helped on my research. My gratitude also goes to Prof Jun-Koo Kang, Prof Chuan Yang Hwang, Prof Wu Yuan, Prof Clive Lennox and Prof Wang Susheng, from whom I received the basic and solid training in financial research. I also want to thank, Prof Gao Huasheng, Prof Angie Low, Prof Sie Ting Lau, Prof Chang Xin, Prof Stephen Dimmock, Prof Wei Chishen, Prof Ru Hong, Prof Zhang Hanjiang and all the other faculty members for their insightful comments during the seminars, from which I learned how to read and improve papers. I'm also grateful to Prof Wu Guiying, who led a reading group on finance and provided lots of support.

I also want to thank my beloved wife Ding Yuan sincerely. She quitted her job in China and moved to Singapore to accompany me through my study and research. Her love and company along the way is a great memory. I'm also grateful to her understanding and support of my pursuit. I would like to thank my parents as well. They have always been very supportive throughout my life.

My gratitude also goes to my friends in Nanyang Business School. In particular, I want to thank Qiao Zheng, Lin Yaheng, Qiang Wei, Yu Yao, Wang Yuxi, Ma Yujing, Yang Bowen, Huang Xiaoran, Liu Na, Li Lingwei, Xie Wenjun, Selvam Srinivasan, Yang Endong, Phua Jing Wen Kenny, Zhang Li, Yan Wangcheng and Lou Pingyi. I benefited a lot from the discussions with them. The special thanks also go to exchange students Ang Sheng, Wen Deer, Zhao Weijie, Li Juan and Liu Chunli. They made my life in Singapore more colourful, and we had a great time. I miss them all. I also want to express my gratitude to my good friend Dou Liyu. During our undergraduate study, we both decided to pursue the research career and went through a lot of hard times together. Though we eventually went to different programs, the chat and sharing in the past years made my PhD life much easier.

Lastly, I want to thank Bee Hua, Karen, Nisha, Florence and all the other management staff, from them I also received a lot of kind help.

Introduction

In essay one, we present a theory of endogenous coalition formation in financial markets, which highlights the information sharing and market competition features of coalitions. Allied members enjoy benefits of information advantage and monopolistic power in trading, but forming coalitions incurs direct costs of setting up coalitions and indirect costs from market liquidity dry-ups. Such a trade-off determines the coalition structure of the economy. As allied members behave more monopolistically, coalitions have negative effects on price informativeness and market liquidity. From the information perspective, financial intermediaries (e.g., asset management companies in the mutual fund industry) can be viewed as coalitions of market players (e.g., fund managers). Our theory provides novel insights about the structure of this industry.

In essay two, we examine the influence of covenant violations on violation firms' alliance activities. We find that firms witness a decline in the number of strategic alliances (especially joint ventures) in the years following debt covenant violations. The causality is established through difference-in-difference regressions and the regression discontinuity design. Our findings support the argument that covenant violation can be detrimental to a firm's reputation, deterring potential partner firms from forming alliances with violation firms. This study contributes to covenant violation research by highlighting the ramifications of reputation damage triggered by covenant violation on corporate alliance activities.

In essay three, we focus on the IPO market, and examine the influence of corporate hedging on firm value. Since corporate hedging reduces information asymmetry of IPO firms, we find that the issuers with corporate hedging have less information to extract from informed

investors and are associated with lower price revision and underwriting fee. More importantly, corporate hedging is found to reduce IPO underpricing, which provides evidence that hedging increases firm value particularly during the issuing process. We also provide further evidence that corporate hedging increases firm value through the channel of reducing information asymmetry and value uncertainty, by documenting that hedging reduces the aftermarket idiosyncratic volatility and enhances aftermarket liquidity and long-term performance.

Table of Contents

Essay One: A Theory of Endogenous Coalition Formation in Financial Markets	1
1. Introduction.....	2
2. The Model.....	6
3. The Equilibrium	9
3.1 Trading Strategy.....	9
3.2 Coalition Formation Strategy.....	13
4. Understanding the Industry Structure of Financial Intermediaries	25
4.1 Firm Size and Performance.....	25
4.2 Technology and Firm Size	26
4.3 The Geography.....	26
5. Conclusions.....	26
References.....	28
Figure 1:A Partial Coalition When $J = 3$	41
Figure 2: A Partial Coalition When $J = 3$: Stability.....	42
Figure 3: A Partial Coalition When $J = 10$ Case 1.....	43
Figure 4: A Partial Coalition When $J = 10$: Case 2.....	44
Figure 5: Welfare Effects of Hypothetical Partial Coalition	45
Figure 6: Minimum Coalition Size: Case 1	46
Figure 7: Minimum Coalition Size: Case 2	47
Figure 8: Optimal Coalition Structure	48
Figure 9: Optimal Number of Coalition.....	49
Figure 10:Optimal Number of Coalition.....	50
Essay Two: Covenant Violation and Strategic Alliances	51
1. Introduction	52
2. Background and Motivation.....	56
2.1. Covenant Violation Research	56
2.2. Strategic Alliance Research.....	57
2.3. Hypothesis	57
3. Data Description and Sample Selection	60
4. Covenant Violation and Alliances Formation.....	61

4.1 Raw Patterns on Alliance Formation Surrounding Covenant Violations.....	61
4.2 Panel Data Evidence	63
4.3 Endogeneity	64
5. Additional Analyses	72
5.1 Attenuating need of Covenant Violating Firm	72
5.2 Reputation and the Relation between Covenant Violation and Alliance Formation.....	72
5.3 Covenant Violation and Announcement Return of Alliance Formation	75
5.4 Firm's Return around Its Partner's Covenant Violation Date	77
6. Conclusions	80
References	82
Table 1: Summary Statistics	84
Table 2: Correlation of Variables Used in Analysis.....	85
Table 3: Raw Patterns on Alliance Formation Surrounding Covenant Violations.....	87
Table 4: Regression of Number of Alliances on Covenant Violation	89
Table 5: Difference-in-Difference Results	93
Table 6: Regression Discontinuity Design (RDD) Results	98
Table 7: The Willingness of Violating Firms to Form Alliances	100
Table 8: Reputation and the Relation between Covenant Violation and Alliance Formation	102
Table 9: Covenant Violation and Announcement Return of Alliance Formation.....	102
Table 10: Firm's cumulative abnormal return around its partner's covenant violation date	107
Appendix: Variable definitions	109
Essay Three: Does Corporate Hedging Affect Firm Value? Evidence from the IPO Market	110
1. Introduction	111
2. Literature Review	113
3. Hypotheses Development.....	116
4. Data and Main Variables.....	118
4.1 Data and Sample Selection	118
4.2 Measures of Corporate Hedging.....	118
4.3 Other variables.....	120

5. Empirical Results	122
5.1 Underwriter and IPO firm hedging.....	122
5.2 Corporate Hedging and IPO Results	124
6. Conclusion.....	130
References	131
Table 1: Summary Statistics	134
Table 2: Hedging and IPO Price Revision.....	136
Table 3: Hedging and Underwriting Fee	137
Table 4: Hedging and IPO Underpricing.....	138
Table 5: Hedging and After-Market Stock Idiosyncratic Volatility	140
Table 6: Hedging and Aftermarket Illiquidity	142
Table 7: Hedging and After-Market IPO Performance	144

Essay One: A Theory of Endogenous Coalition Formation in Financial Markets

Abstract

We present a theory of endogenous coalition formation in financial markets, which highlights the information sharing and market competition features of coalitions. Allied members enjoy benefits of information advantage and monopolistic power in trading, but forming coalitions incurs direct costs of setting up coalitions and indirect costs from market liquidity dry-ups. Such a trade-off determines the coalition structure of the economy. As allied members behave more monopolistically, coalitions have negative effects on price informativeness and market liquidity. From the information perspective, financial intermediaries (e.g., asset management companies in the mutual fund industry) can be viewed as coalitions of market players (e.g., fund managers). Our theory provides novel insights about the structure of this industry.

JEL Classification: G14; G23; L22

Keywords: Coalition; Financial Intermediaries; Information; Market Competition

1 Introduction

Numerous empirical evidence suggests that networks facilitate information sharing and coordination among market participants.¹ Existing theories on networks in financial markets, including Colla and Mele (2010), Ozsoylev and Walden (2011), Han and Yang (2013), and Cao and Ye (2014), treat these networks as exogenously given and proceed to examine their implications for financial market outcomes. In contrast, working from an information sharing and market competition perspective, we present a theory of endogenous coalition formation decisions by market players to study the coalition structure. We try to address the following questions. What kind of players, for example, well-informed traders or poorly-informed traders, tend to join a coalition? How many investors will join a coalition? As the advance of information technology expedites information processing and dissemination, how does it affect the coalition size (which is measured by the number of investors in a coalition) and the number of coalitions in the economy?

A natural framework to study coalition formation in financial markets is a multi-trader generalization of Kyle (1985).² The elements are a risky asset (the stock), multiple informed traders, a market maker, and a liquidity trader. We modify this framework by

¹Networks could be loosely formed by the cultural, educational, religious, or even geographical reasons, or well organized ones like mutual fund managers in the same fund family. For example, Grinblatt and Keloharju (2001) find that investors are more likely to hold, buy, and sell stocks of firms that are located close to them, that communicate in their native tongue, and that have chief executives of the same cultural background. Hong et al. (2004) find that social households-those who interact with their neighbors, or attend church-are more likely to invest in the stock market when their peers participate. Hong et al. (2005) find that mutual fund managers are more likely to buy or sell a particular stock if other managers in the same city are buying or selling that stock, which suggests that investors spread information about stocks to one another by word of mouth. Ivković and Weisbenner (2007) find that households are more likely to buy stocks from an industry if their neighbors are buying stocks from the same industry. Cohen et al. (2008) find that mutual fund managers are more likely to buy stocks of firms that have board members of the same education background. Nanda et al. (2004), Gaspar et al. (2006), Elton et al. (2007), and Bhattacharya et al. (2013) show that sibling mutual funds in the same family tend to coordinate trades.

²Kyle's (1985) setup provides analytical tractability and has been used extensively in the microstructure literature (e.g., Holden and Subrahmanyam, 1992; Foster and Viswanathan, 1996; and Back et al., 2000).

allowing informed traders to endogenously choose whether to form a coalition with other informed traders, in which case they will combine resources so that they not only share information but also coordinate trades. The benefit of forming a coalition is that allied members gain information advantage and monopolistic power in trading. However, the coalition has two types of costs. First, there can be direct costs, such as costs related to search, setup, and coordination efforts. Second, there can be an indirect cost. As the coalition gains monopolistic power and behaves more strategically, the market maker lowers market liquidity to break even. This dries up market liquidity. Thus, in our model, whether to form a coalition is an endogenous decision that informed traders make after weighing the benefits and costs. It is possible that all informed traders form a comprehensive coalition. It is also possible that some informed traders form several smaller coalitions, while other informed traders choose to remain independent.

A simple cost-benefit analysis suggests that for a coalition to prevail, it must significantly improve the allied members' information advantage and/or reduce competition. The main results of our model on the coalition structure are consistent with this intuition. First, a coalition is likely to be formed by informed traders with the best-quality information. Second, a coalition, if formed, must be sufficiently large. Third, as the average information quality increases, the coalition size (i.e., the number of informed traders in a coalition) increases and, accordingly, the number of coalitions decreases. Fourth, if there are different groups of informed traders living in separate "islands," so they can form coalitions only within each group, then a small number of large coalitions are likely to emerge from the group of informed traders with good-quality information and the group of informed traders with a large population.³

We further use our model to obtain new insights about the industry structure of fi-

³This separate "island" setup is often used by the social-network literature (see Jackson, 2010, for a survey).

nancial intermediaries. From the information perspective, financial intermediaries can be viewed as sets of coalitions. Particularly, an asset management company in the mutual fund industry can be viewed as a coalition of several fund managers.⁴ Our model implies that a big asset management company is likely to include fund managers with the best-quality information. Therefore, mutual funds affiliated with big asset management companies tend to outperform those affiliated with small asset management companies.⁵ Moreover, as the advance of information technology expedites information processing and dissemination, which improves the average information quality, in recent decades, industry consolidation has led to the emergence of super big asset management companies such as BlackRock. Finally, big asset management companies tend to arise in metropolitan areas in which there is a large population and investors receive good-quality information. Areas that fit the description include Boston, Chicago, New York, Philadelphia, Los Angeles, and San Francisco.

Our study belongs to the growing literature on networks in financial markets. Existing theories, including Colla and Mele (2010), Ozsoylev and Walden (2011), Han and Yang (2013), and Cao and Ye (2014), assume that informed traders share information through exogenously given networks, and examine the implications of networks for financial market outcomes. We depart from the literature by allowing market players to choose endogenously whether to form coalitions after weighing the benefits and costs. Our analysis is focused on the coalition structure of the economy.

Our prediction on the implication of information networks for financial market out-

⁴Consistent with this view, Bhojraj et al. (2012) show that sibling mutual funds in the same company tend to share information. Nanda et al. (2004), Gaspar et al. (2006), Elton et al. (2007), and Bhattacharya et al. (2013) show that sibling mutual funds in the same company tend to coordinate trades.

Other financial intermediaries can also be viewed as sets of coalitions. For example, a brokerage house can be viewed as a coalition of financial analysts.

⁵This is consistent with the empirical findings of Chen et al. (2004), Pollet and Wilson (2008), and Bhojraj et al. (2012).

comes also differs from those of existing theories. In our model, coalitions increase informed traders' monopolistic power. As they trade more strategically, the informational efficiency of stock prices and market liquidity decrease. In contrast, in Colla and Mele (2010) and Ozsoylev and Walden (2011), information networks lower informed traders' monopolistic power. As informed traders trade more competitively, the informational efficiency of stock prices and market liquidity improve. Han and Yang (2013) show that investors may find it too costly to acquire information by themselves if they can free-ride peers through connections. Thus, networks can lower the total amount of information in the financial markets and, thereafter, the informational efficiency of stock prices. Empirically, their prediction of the negative effect of networks on the informational efficiency of stock prices mostly applies to small stocks, young stocks, and risky stocks, among which information acquisition costs are high.

Our study is also related to the economics literature on strategic network formation.⁶ Existing theories on network formation of financial institutions are predominantly focused on the banking sector.⁷ Little is known about network formation in other sectors such as the mutual fund industry. Our study fills the void. We argue that asset management companies in the mutual fund industry can be viewed as coalitions endogenously chosen by fund managers in pursuit of information advantage and monopolistic power in trading. This interpretation fits some important aspects of this industry. Our model provides novel insights about the structure of this industry.

Existing theories on delegated asset management, including Ou-Yang (2003), Palomino and Prat (2003), Gervais et al. (2005), Dybvig et al. (2010), Vayanos and Woolley (2013),

⁶For theories in general settings, see, for example, Jackson and Wolinsky (1996), Bala and Goyal (2000), and Hojman and Szeidl (2006, 2008). Jackson (2010), and Allen and Babus (2009) provide excellent surveys.

⁷See, for example, Blume et al. (2011), Allen et al. (2012), Cabrales et al. (2012), Acemoglu et al. (2013), Babus (2013), Zawadowski (2013), Bluhm et al. (2013), and Farboodi (2015).

and He and Xiong (2013), are focused on the design of the optimal contracts to incentivize fund managers to alleviate the agency problem at the fund level. They typically assume that fund managers work for the asset management companies, the structure of which is given exogenously.

We organize the rest of the article as follows. Section 2 describes our model. Section 3 solves for the equilibrium and then derives its properties. Section 4 applies the predictions of our model to study the industry structure of financial intermediaries. Section 5 concludes.

2 The Model

We develop our model based on a multi-trader generalization of Kyle (1985). Consider a simple exchange economy. There are three dates, -1, 0, and 1. There is one risky asset, a stock. The stock pays $\bar{F} + X$ at date 1. $\bar{F}$ is a positive constant. X is a random variable that follows a standard normal distribution; that is, $X \sim N(0, 1)$. The stock price at date 0 is denoted as P , which is to be determined.

There are three types of risk-neutral players. First, there are J informed traders. At period 0, each informed trader, indexed by j , observes a private signal about the payoff of the stock, $S_j = X + \epsilon_j$. ϵ_j follows a normal distribution with mean zero and variance v_j ; that is, $\epsilon_j \sim N(0, v_j)$. She submits a market order, D_j , which is to be determined. We assume that $\forall i \neq j$, ϵ_i is independent of ϵ_j .

Second, there is a liquidity trader. She submits a market order, Z , which follows a normal distribution with mean zero and variance σ_z^2 ; that is, $Z \sim N(0, \sigma_z^2)$. We assume that Z is independent of X and ϵ_j , $\forall j$.

Third, there is a market maker. She receives the aggregate market order, $D = \sum_j D_j + Z$, and sets the stock price, P . The market maker faces perfect competition from other

market makers, so she has zero expected profits. This implies that $P = \bar{F} + E[X|D]$.

The novel feature of our model is that at date -1, informed traders decide whether to ally with peers. If they do, then they not only exchange information truthfully but also coordinate trades. A coalition, which does not necessarily include all informed traders, is indicated by a set A .

Here we assume that within a coalition, informed traders will tell each other their information truthfully. There are various mechanisms to ensure this. Take the coalition formed among neighbors or alumni as an example. There can be a severe reputation loss if a member is caught in a lie. It is also possible that allied members' payoffs are aligned, so they have no incentives to lie. This tends to happen among professional money managers in the same asset management company because their compensations are often partially linked to company performance. Finally, some institutional features might prevent such deviation activities. For example, the SEC prohibits cross trades between sibling funds in the same family that may cause conflicts of interests.

Coordination of trades is a key ingredient of our model. Stein (2008) points out that in general, if informed traders cannot coordinate trades, then they will not exchange information either. The intuition for this is that information exchange will lower their information advantage. What's more, receivers of this information may even use it when trading against those who provided it. Colla and Mele (2010) explain this intuition in more details. They argue that private information gives informed traders monopolistic power. If informed traders exchange information but don't coordinate trades, then their monopolistic power weakens, so they will trade more aggressively to preempt peers. It can be shown that their payoff will decrease. Therefore, they will not exchange information in the first place.

Forming a coalition, A , causes direct costs, $C(A)$, due to search, setup, and coordination

efforts. In general, $C(A)$ increases with the extent and complexity of the coalition, A , which can be measured using the number of informed traders in the coalition. Allied members in the coalition share the costs and benefits of the coalition based on the Shapley (1953) value, which captures their contributions to the coalition. In our model, an allied member's Shapley value is proportional to her information precision, $1/v_j$.

We summarize the timeline of our model as follows.

Date -1: (Coalition Formation Stage) Informed traders decide whether to form a coalition, A , which does not necessarily include all informed traders.

Date 0: (Trading Stage) Each informed trader, j , receives her private information, S_j . Informed traders in the coalition, $j \in A$, share their private information, S_j , and coordinate trades. The coalition submits a market order, D_A . Each independent informed trader, $j \notin A$, submits a market order, D_j , based on her private information, S_j . The liquidity trader submits a market order, Z . After receiving the aggregate market order, $D = D_A + \sum_{j \notin A} D_j + Z$, the market maker sets the stock price, P .

Date 1: (Final Stage) The stock pays $\bar{F} + X$, which is distributed to every player according to her holdings.

In our model, whether to form a coalition so that they can exchange information and coordinate trades is an endogenous decision that informed traders make after weighing the benefits and costs. It is possible that all informed traders form a comprehensive coalition. It is also possible that some informed traders form several smaller coalitions, while other informed traders choose to remain independent.

3 The Equilibrium

We solve for the equilibrium using backward induction. In Section 3.1, we focus on the trading stage at date 0. We suppose that a coalition, A , has already been formed and solve for every player's optimal trading strategy. Our analysis can easily be extended to include multiple coalitions. In Section 3.2, we focus on the coalition formation stage at date -1, where we study what kind of informed traders form a coalition, how big a coalition can be, and how many coalitions can be formed.

3.1 Trading Stage

3.1.1 Trading with No Coalition

Before jumping to the case with coalitions, we first study a benchmark case in which there is no coalition, so all informed investors compete against each other.

Proposition 1. *Consider the case with no coalition of informed traders, which is denoted by (NA) . There is a linear equilibrium in which the market maker sets the stock price according to $P(NA) = \bar{F} + \lambda(NA)D$, and each informed trader submits a market order $D_j(NA) = \theta_j(NA)S_j$. $\lambda(NA)$ and $\theta_j(NA)$ are given by:*

$$\begin{aligned}\lambda(NA) &= \frac{K(NA)/\sigma_z}{1 + \sum_j \frac{1}{1 + 2v_j}}, \\ \theta_j(NA) &= \frac{\sigma_z/K(NA)}{1 + 2v_j},\end{aligned}$$

where $K(NA) = \sqrt{\sum_j \frac{1 + v_j}{(1 + 2v_j)^2}}$.

Proof: See the Appendix.

To understand this equilibrium, we consider the following special case, which Holden and Subrahmanyam (1992) have studied. The intuitions we obtain in this special case help us understand the equilibrium when there are coalitions of informed traders.

A special case: Let $v_j = V$, $\forall j$, so every informed trader has the same-quality information. Denote the informativeness of the stock price as $\text{Var}(X|P)$. It is straightforward to show that

$$\begin{aligned}\text{Var}(X|P(NA)) &= \frac{1}{1 + J/(1 + 2V)}, \\ \theta_j(NA) &= \frac{\sigma_z}{\sqrt{J(1 + V)}}, \\ \lambda(NA) &= \frac{\sqrt{J(1 + V)}/\sigma_z}{1 + 2V + J}.\end{aligned}$$

A decrease in J has three consequences. First, the informativeness of the stock price decreases (high $\text{Var}(X|P)$). There are two reasons for this. One reason is that as J decreases, the sources of information decrease, which lowers the total amount of information in the market. The other reason is that there is less competition among informed traders, so they behave more monopolistically. Their trades reveal less information to the market. Second, informed traders trade more aggressively (high θ_j). This is because as the competition decreases, informed traders are less subject to the winner's curse problem. Third, market liquidity decreases (high λ) for sufficiently large J , such as $J > 1 + 2V$. This is because as informed traders behave more monopolistically, the market maker must increase λ to break even.

An increase in informed traders' information quality (i.e., V decreases) also has three consequences. First, the price informativeness increases (low $\text{Var}(X|P)$). This is because informed traders reveal more precise information through trades to the stock price. Second,

informed traders trade more aggressively (high θ_j). This is because they are more confident in their own information. Third, market liquidity decreases (high λ) if informed traders' information is not very precise, such as $3 + 2V > J$. This is because the market maker faces a more severe information disadvantage and must increase λ to break even.

3.1.2 Trading with a Coalition

Suppose that a coalition of some informed traders, A , has been formed. Denote

$$S_A = \frac{\sum_{j \in A} \frac{S_j}{v_j}}{\sum_{j \in A} \frac{1}{v_j}} = X + \epsilon_A.$$

$\epsilon_A = \frac{\sum_{j \in A} \frac{\epsilon_j}{v_j}}{\sum_{j \in A} \frac{1}{v_j}}$ follows a normal distribution with mean zero and variance $v_A = 1 / \sum_{j \in A} \frac{1}{v_j}$; that is, $\epsilon_A \sim N(0, v_A)$.

Lemma 1. *As far as X is concerned, S_A is a sufficient statistic of $\{S_j : j \in A\}$.*

Proof: See the Appendix.

An implication of this lemma is that we can treat the coalition, A , as one informed trader who observes a private signal S_A . In the following proposition, we use this idea to describe the coalition's demand for the stock.

Proposition 2. *Consider the case with a coalition of informed traders, which is denoted by (A) . There is a linear equilibrium in which the market maker sets the stock price according to $P(A) = \bar{F} + \lambda(A)D$, the coalition submits a market order $D_A(A) = \theta_A(A)S_A$,*

and every other informed trader, $j \notin A$, submits a market order $D_j(A) = \theta_j(A)S_j$. $\lambda(A)$, $\theta_A(A)$, and $\theta_j(A)$ are given by:

$$\begin{aligned}\lambda(A) &= \frac{K(A)/\sigma_z}{1 + \frac{1}{1+2v_A} + \sum_{j \notin A} \frac{1}{1+2v_j}}, \\ \theta_A(A) &= \frac{\sigma_z/K(A)}{1+2v_A}, \\ \theta_j(A) &= \frac{\sigma_z/K(A)}{1+2v_j}, \quad \forall j \notin A,\end{aligned}$$

where $K(A) = \sqrt{\frac{1+v_A}{(1+2v_A)^2} + \sum_{j \notin A} \frac{1+v_j}{(1+2v_j)^2}}$.

Proof: See the Appendix.

The following corollary describes the monotonic properties of the equilibrium with respect to the coalition size.

Corollary 1. *Suppose that the coalition expands from A to A' , where $A' = A \cup \{b\}$ and $b \notin A$. Then,*

- (i) *the stock price becomes less informative; that is, $\text{Var}(X|P(A')) > \text{Var}(X|P(A))$;*
- (ii) *market liquidity decreases; that is, $\lambda(A') > \lambda(A)$;*
- (iii) *informed traders bid more aggressively; that is, $\theta_{A'}(A') > \theta_A(A)$ and $\theta_j(A') > \theta_j(A)$, $\forall j \notin A'$.*

Proof: See the Appendix.

Intuitively, the expansion of the coalition reduces the effective number of informed traders. Then, as the special case in the last subsection suggests, this reduces the intensity

of competition among informed traders. As informed traders both inside and outside the coalition behave more monopolistically, they trade more aggressively but release less information to the market. Therefore, the stock price becomes less informative. The market maker must increase λ , the sensitivity of the stock price to the market order she receives, to break even. This lowers market liquidity.

Corollary 1 suggests that networks, in the form of coalitions, in the financial markets can have negative effects on the informativeness of stock prices and on market liquidity. This market liquidity dry-up represents an indirect but important cost of forming a coalition.

3.2 Coalition Formation Stage

To study the coalition formation, we need to look at the effects of a coalition of informed traders, A , on each player's ex ante (date -1) payoff. An immediate observation is that the coalition has no effect on the market maker's ex ante payoff because on average, her payoff is always 0.

For other players, in the case with no coalition of informed traders, denote $E\Pi_j(NA)$ and $E\Pi_L(NA)$ as the ex ante payoffs to each informed trader and the liquidity trader. It follows from the proof of Proposition 1 that

$$\begin{aligned} E\Pi_j(NA) &= E\left[E\left[(\bar{F} + X - P(NA)) \cdot D_j(NA) \middle| S_j\right]\right] = \lambda(NA)\theta_j^2(NA)(1 + v_j), \\ E\Pi_L(NA) &= E\left[(\bar{F} + X - P(NA)) \cdot Z\right] = -\lambda(NA)\sigma_z^2. \end{aligned}$$

In the case with a coalition of informed traders, A , denote $E\Pi_A(A)$, $E\Pi_j(A)$ ($\forall j \notin A$), and $E\Pi_L(A)$ as the ex ante payoffs to the coalition, each independent informed trader,

and the liquidity trader. It is straightforward to show that

$$\begin{aligned}
E\Pi_A(A) &= E\left[E\left[(\bar{F} + X - P(A)) \cdot D_A(A) \middle| S_A\right]\right] = \lambda(A)\theta_A^2(A)(1 + v_A), \\
E\Pi_j(A) &= E\left[E\left[(\bar{F} + X - P(A)) \cdot D_j(A) \middle| S_j\right]\right] = \lambda(A)\theta_j^2(A)(1 + v_j), \forall j \notin A, \\
E\Pi_L(A) &= E\left[(\bar{F} + X - P(A)) \cdot Z\right] = -\lambda(A)\sigma_z^2.
\end{aligned}$$

Use $\Gamma_A(A)$, $\Gamma_j(A)$ ($\forall j \notin A$), and $\Gamma_L(A)$ to describe the effects of the coalition on the ex ante payoffs to the coalition, each independent informed trader, and the liquidity trader.

$$\begin{aligned}
\Gamma_A(A) &= E\Pi_A(A) - \sum_{j \in A} E\Pi_j(NA), \\
\Gamma_j(A) &= E\Pi_j(A) - E\Pi_j(NA), \quad \forall j \notin A, \\
\Gamma_L(A) &= E\Pi_L(A) - E\Pi_L(NA).
\end{aligned}$$

Coalition members share the coalition synergy, based on the Shapley value:

$$\Gamma_j(A) = \frac{\frac{1}{v_j}}{\sum_{j \in A} \frac{1}{v_j}} \Gamma_A(A), \quad \forall j \in A.$$

Corollary 2. (i) *The coalition increases the ex ante payoff to independent informed traders (if any); that is, $\Gamma_j(A) > 0$, $j \notin A$.*

(ii) *The coalition decreases the ex ante payoff to the liquidity trader; that is, $\Gamma_L(A) < 0$.*

Proof: See the Appendix.

A coalition has three effects on an independent informed trader's ex ante payoff. First, it reduces competition among informed traders, which increases her payoff. Second, it represents a stronger competitor, which decreases her payoff. Third, it leads to dry-ups

of market liquidity, which also decreases her payoff. Part (i) of Corollary 2 suggests that the first effect dominates the other two effects. Thus, the net effect of a coalition on an independent informed trader's payoff is positive.

Part (ii) of Corollary 2 suggests that a coalition has a negative effect on the liquidity trader's payoff. This is because the coalition causes dry-ups of market liquidity.

Does a coalition increase the ex ante payoff to allied members in the coalition? The answer to this question is not obvious. On one hand, a coalition reduces competition and improves the allied members' information advantage (relative to that of independent informed traders), which increases their payoff. On the other hand, a coalition also causes direct costs due to search, setup, and coordination efforts, which are represented by $C(A)$, and an indirect cost from dry-ups of market liquidity, which decreases their payoff. We are not able to obtain a clear comparison between the benefits and costs of form coalitions except in the following two polar cases regarding $C(A)$.

Two Polar Cases: In the first polar case, it is prohibitively costly to form a coalition (i.e., $C(A) \rightarrow \infty, \forall A$). In this case, any possible gains from the coalition will be outweighed by the high costs; that is, $\Gamma_A(A) \leq C(A)$. Therefore, no coalition of informed traders will be formed.

In the second polar case, the cost to form a coalition is negligible (i.e., $C(A) \rightarrow 0, \forall A$). In this case, a coalition that includes all informed traders will be formed. We refer to this coalition as a comprehensive coalition. One may wonder whether an informed trader prefers to leave the coalition and remain independent. We can show that if all other informed traders stay in the coalition, then she will also stay in the coalition. Therefore, a comprehensive coalition is sustained as a Nash equilibrium.

In what follows, we assume that $C(A)$ is prohibitively high for a comprehensive coal-

tion, but reasonably low for a partial coalition. This allows us to focus on the partial coalition(s). We use a numerical analysis to examine under what conditions a partial coalition can improve the payoff of allied members, so they will form a partial coalition.⁸ We consider cases with different levels of information quality, V , and/or different numbers of informed traders, J . This allows us to examine the impacts of information and competition on our results.

3.2.1 Who Joins a Partial Coalition?

Consider a simple economy in which there are only $J = 3$ informed traders. Let $v_1 \leq v_2 \leq v_3$, so they are ordered by their information quality. Suppose that the cost function, $C(A)$, satisfies mild conditions, which allows only a partial coalition of two informed traders. Who will join the coalition?

There can be three scenarios for the coalition structure.

(S1) $\{1, 2, 3\}$ indicates that every informed trader remains independent.

(S2) $\{\{1, 2\}, 3\}$ indicates that informed traders 1 and 2 form a coalition.

(S3) $\{\{1, 3\}, 2\}$ indicates that informed traders 1 and 3 form a coalition.

(S4) $\{1, \{2, 3\}\}$ indicates that informed traders 2 and 3 form a coalition.

In general, there can be multiple equilibria for a game with three or more players. To simplify our analysis, we follow Jackson and Wolinsky (1996) to give two definitions about the equilibrium.⁹

⁸We use numerical analysis to illustrate the coalition structure of the economy because we are not able to obtain the analytical solution to our model. We have varied our numerical analysis to verify the robustness of our main results.

⁹Farboodi (2014) uses a similar approach to define the network equilibrium in the banking sector.

Definition 1. *A coalition, A , is admissible if it provides a positive synergy, $\Gamma(A) > 0$.*

Definition 2. *A coalition, A , is stable if no player in the coalition prefers to leave.*

A simple cost-benefit analysis suggests that for a partial coalition to prevail, it must significantly improve the allied members' information advantage and/or reduce competition. In this simple economy with three informed traders, all partial coalitions include two informed traders, so they reduce competition to the same degree. Therefore, the prevailing partial coalition hinges solely on its information advantage. This implies that the partial coalition should include informed traders with the best-quality information. Informed traders with the poorest-quality information should remain independent. The following corollary is consistent with this intuition.

Corollary 3. *Consider a simple economy with $J = 3$ and $v_1 \leq v_2 \leq v_3$.*

- (i) *A coalition between information traders 2 and 3 is not admissible because it produces a negative synergy; that is, $\Gamma_A(A = \{2, 3\}) \leq 0$.*
- (ii) *A coalition between informed traders 1 and 2 produces a higher synergy than a coalition between informed traders 1 and 3; that is, $\Gamma_A(A = \{1, 2\}) \geq \Gamma_A(A = \{1, 3\})$.*
- (iii) *Informed trader 1 receives more benefit from a coalition with informed trader 2 than from a coalition with informed trader 3; that is, $\Gamma_1(A = \{1, 2\}) \equiv \frac{1/v_1}{1/v_1 + 1/v_2} \Gamma_A(A = \{1, 2\}) \geq \Gamma_1(A = \{1, 3\}) \equiv \frac{1/v_1}{1/v_1 + 1/v_3} \Gamma_A(A = \{1, 3\})$.*

Proof: See the Appendix.

Part (i) of Corollary 3 rules out the partial coalition of informed traders 2 and 3 because this coalition produces a negative synergy. Parts (ii) and (iii) suggest that the partial coalition, $A = \{1, 2\}$, is likely to prevail not only because it produces a higher

synergy but also because it is preferred by informed trader 1 as she gains more from the synergy of this coalition, according to the Shapley value. For it to be admissible, it must be

$$\Gamma_A(A = \{1, 2\}) \geq \max(0, \Gamma_A(A = \{1, 3\}), \Gamma_A(A = \{2, 3\})). \quad (1)$$

Figure 1 depicts the admissible coalition, $A = \{1, 2\}$, using a numerical analysis. We let $1 = v_1 \leq v_2 \leq v_3 \leq 40$. In the shaded area, Eq. (1) holds, so the partial coalition, $A = \{1, 2\}$, is admissible. Note that this area features a high value of v_3 (≥ 3.5). Therefore, a partial coalition can prevail only if the independent informed traders do not have very precise information. This also confirms our intuition that a partial coalition increases the payoff to the allied informed players when it significantly improves the allied informed traders' information advantage.

[Insert Figure 1 here.]

Part (iii) of Corollary 3 indicates that informed trader 1 prefers to ally with informed trader 2. For the partial coalition, $A = \{1, 2\}$, to be stable, informed trader 2 should have no incentive to leave the coalition. Jackson and Wolinsky (1996) suggest a condition in addition to Eq. (1).

$$\Gamma_2(A = \{1, 2\}) \equiv \frac{1/v_2}{1/v_1 + 1/v_2} \Gamma_A(A = \{1, 2\}) \geq \Gamma_2(A = \{1, 3\}). \quad (2)$$

This equation ensures that informed trader 2 gains more from staying in the coalition than from becoming independent while letting informed traders 1 and 3 form a coalition.

[Insert Figure 2 here.]

Figure 2 shows that in the dark-shaded area, the coalition, $A = \{1, 2\}$, is stable. In the light-shaded area, the coalition, $A = \{1, 2\}$, is fragile, so informed trader 2 may leave

the coalition. There are two notable observations. First, the stable area features a higher v_3 than the fragile area does. This suggests that to be stable, a coalition needs to have a significant information advantage (relative to informed trader 3). Second, the stable area also features a much smaller v_2 . This suggests that to be stable, the two informed traders, 1 and 2, in the coalition must have similar-quality information, so they have a similar share of the coalition synergy.

[Insert Figure 3 here.]

In what follows, we restrict our attention to the admissibility of the partial coalition, $A = \{1, 2\}$. Figure 3 considers a more general case. There are $J = 10$ informed traders. Their information qualities satisfy $1 = v_1 \leq v_2 \leq v_3 \leq 20$ and $v_j = 50, \forall j > 3$. The shaded area, which features a higher value of v_3 (≥ 6.5), satisfies Eq. (1), so the coalition $A = \{1, 2\}$ is admissible in this area. An interesting observation from comparing Figures 3 and 1 is that as J increases, independent informed trader 3 must have poorer information quality for the partial coalition $A = \{1, 2\}$ to be admissible. This is because as there are more independent informed traders, independent informed trader 3 must have poorer information quality, so that the coalition $A = \{1, 2\}$ can maintain sufficient information advantage to make a profit.

[Insert Figure 4 here.]

In Figure 4, we let $v_j = 35, \forall j > 3$, so these informed traders have relatively better information quality than those in Figure 3. Compared with Figure 3, the shaded area, in which the coalition $A = \{1, 2\}$ is admissible, shifts farther upwards. This area features an even higher value of v_3 (≥ 9.5). This is because as independent informed traders $j > 3$ have better information quality, independent informed trader 3 must have even

poorer information quality, so the coalition $A = \{1, 2\}$ can maintain sufficient information advantage to make a profit.

Prediction 1. *A partial coalition tends to be formed by informed traders with the best-quality information.*

3.2.2 Minimum Coalition Size

Consider a symmetric case in which $v_j = V, \forall j$, so all informed traders have the same-quality information. Figures 1 to 4 suggest that in this symmetric case, a small partial coalition $A = \{1, 2\}$ won't be formed because it does not significantly reduce competition and gain information advantage. Figure 5 confirms this. Suppose that there can be only one coalition. Panel (a) shows that if formed, the partial coalition $A = \{1, 2\}$ will have a negative synergy (i.e., $\Gamma_A(A = \{1, 2\}) < 0$). Panel (b) shows that consistent with Corollary 2, independent informed traders generally gain from this coalition (i.e., $\Gamma_j(A = \{1, 2\}) > 0, \forall j \geq 3$).

[Insert Figure 5 here.]

Our above cost-benefit analysis suggests that for a partial coalition to be admissible, it needs to be sufficiently large because only a large coalition can significantly reduce competition and obtain information advantage. The minimum size of an admissible coalition, $\underline{m}$, can be obtained as follows:

$$\begin{aligned} \min_m \quad & m \\ \text{s.t.} \quad & \Gamma_A(A = \{1, 2, \dots, m\}) \geq 0. \end{aligned}$$

Figure 6 plots $\underline{m}$ depending on the information quality. We assume that there are $J = 40$ informed traders, each of whom has the same-quality information, $v_j = V, \forall j$.

Here we allow for multiple coalitions. Because of symmetry, every coalition should have the same number of informed players. There are two notable observations. First, $\underline{m}$ increases with the information quality, V . For example, $\underline{m}$ for a single coalition is 27 when $V = 10$, and it increases to 30 when $V = 5$. This is because as other informed traders have good-quality information, the coalition must be sufficiently large to reduce competition and gain information advantage. Second, $\underline{m}$ decreases with the number of coalitions. This suggests that coalitions can have an externality effect on one another because each coalition lowers the intensity of competition in the market, benefiting other coalitions. This lowers the minimum size of a coalition.

[Insert Figure 6 here.]

Figure 7 plots $\underline{m}$ depending on the number of coalitions. We assume that there can be $J = 20, 30$, and 40 informed traders. Consistent with Figure 6, $\underline{m}$ decreases in the number of coalitions. Moreover, $\underline{m}$ increases in the total number of informed traders. This is because when there are many informed traders, a coalition must be sufficiently large to reduce competition and gain information advantage.

[Insert Figure 7 here.]

Prediction 2. *A coalition, if formed, must be sufficiently large.*

3.2.3 Optimal Coalition Structure

Now we study the optimal coalition structure. To simplify our analysis, we let $v_j = V, \forall j$, so all informed traders have the same-quality information. We follow Dessein and Santos (2006) to assume a quadratic cost function for a coalition:

$$C(A(m)) = \gamma(m - 1)^2,$$

where m represents the number of allied informed traders in the coalition. γ is a constant.

By symmetry, there can be n coalitions, each of which has m informed traders.¹⁰ Allied members have the same Shapley value, so they share the coalition synergy equally. We define the optimal coalition structure of the economy as follows.

Definition 3. *Consider a symmetric economy, in which $v_j = V$, $\forall j$, so all informed traders have the same-quality information. A coalition structure of the economy, $\{m, n\}$, is optimal if it maximizes the average coalition member's net gain, that is,*

$$\max_{m,n} \frac{1}{m} [\Gamma_A(A = \{1, 2, \dots, m\}) - C(A(m))].$$

This optimal coalition structure, $\{m, n\}$, can sustain as an equilibrium if any allied player's deviation from this structure leads to the collapse of the structure and the only off-equilibrium outcome is that every informed player stays independent. Admittedly, there can be other equilibria. We shy away from the other equilibria for two reasons. First, there is little tractability of these equilibria. Second, from the perspectives of informed traders, these equilibria are obviously *Pareto* dominated by the optimal coalition structure we consider here.

In Figure 8, we assume that there can be $J = 30$ or 40 informed traders. We let $C(A(m)) = 10^{-4}(m-1)^2$. Panels (a) and (b) show that as the information quality improves (low V), the optimal coalition size, m , increases, and the optimal number of coalitions, n , decreases. The intuition for these results is as follows. As informed traders have good-quality information, only large coalitions can significantly reduce competition and gain information advantage, leading to a profit. Therefore, the optimal coalition size should

¹⁰If the total number of informed traders, J , is not divisible by n , then there will be some residual informed traders. We assume that they remain independent.

increase. This also leads to a smaller number of coalitions because in this simple example, the population of informed traders is constant.

Panels (a) and (b) also show that as the number of informed traders increases (high J), the optimal coalition size may or may not increase, but the number of coalitions generally increases. Intuitively, a larger number of coalitions implies that the competition is significantly reduced, so the coalitions can make a profit.

[Insert Figure 8 here.]

Prediction 3. *As information quality improves, the optimal coalition size increases and the number of coalitions decreases.*

Next, we consider the case in which there are two groups of informed traders, indexed by the subscripts 1 and 2, in the economy. Informed traders from the same group have the same-quality information. Specifically, if informed trader j is in group 1 (group 2), then $v_j = V_1$ ($v_j = V_2$). We follow the social-network literature (e.g., Jackson, 2008) to assume that the two groups of informed traders live in two separate “islands,” so they can form coalitions only within each group. In our framework, this requires that the costs of maintaining an across-group coalition, which can be related to monitoring and enforcing, be prohibitively high.

By symmetry, in group 1 (2), there can be n_1 (n_2) coalitions, each of which has m_1 (m_2) informed traders. In a similar vein as our Definition 3 on optimality (see above), we assume that the two groups are equally weighted in the sense that the optimal coalition structure m_1, m_2, n_1, n_2 maximizes the net gains of the average coalition member from each group:

$$\max_{m_1, m_2, n_1, n_2} \frac{1}{m_1} \left[\Gamma_A(A = \{1, \dots, m_1\}) - C(A(m_1)) \right] + \frac{1}{m_2} \left[\Gamma_A(A = \{1, \dots, m_2\}) - C(A(m_2)) \right].$$

[Insert Figure 9 here.]

In Figure 9, we assume that each group has 40 informed traders. Informed traders in group 1 have better-quality information than those in group 2; specifically, $V_1 = 1$ and $V_2 > 1$. We also let $C(A(m)) = 10^{-4}(m - 1)^2$. Panels (a) and (b) show that group 1 has a larger optimal coalition size but a smaller number of coalitions than group 2 does. The intuition for these results is as follows. As informed traders in group 1 have relatively good-quality information, only large coalitions can significantly reduce competition and gain information advantage, leading to a profit. Therefore, group 1 should have a larger coalition size, which also leads to a smaller number of coalitions. By significantly reducing competition in the whole economy, group 1's coalition structure, large m and small n , also has a spillover effect on group 2's coalition structure. Group 2's optimal coalition size doesn't need to be very large, but the coalitions can still make a profit.

[Insert Figure 10 here.]

In Figure 10, we assume that there are more informed traders in group 1 than in group 2; that is, $J_1 > 100$ and $J_2 = 100$. We let all informed traders have the same-quality information, $V_1 = V_2 = 5$. Also, $C(A(m)) = 10^{-5}(m - 1)^2$. Panels (a) and (b) show that group 1 has a large optimal coalition size but a smaller number of coalitions than group 2 does.¹¹ The intuition for these results is similar to that for the case in Figure 9. As there are more informed traders in group 1, only large coalitions can significantly reduce competition and gain information advantage, leading to a profit. Therefore, group 1 should have a larger coalition size, which also leads to a smaller number of coalitions. By significantly reducing competition in the whole economy, group 1's coalition structure, large m and small n , also has a spillover effect on group 2's coalition structure. Group

¹¹Note that there are some bumps in the plots, due to the nature of integer programming.

2's optimal coalition size doesn't need to be very large, but the coalitions can still make a profit.

Prediction 4. *A small number of large coalitions are likely to originate from the group of informed traders who possess good-quality information and the group of informed traders with a large population.*

4 Understanding the Industry Structure of Financial Intermediaries

In this section, we use our theory to obtain new insights about the industry structure of financial intermediaries. We are particularly interested in the mutual fund industry because after experiencing rapid growth in the past decades, this industry has become one of the most important financial intermediaries. Toward the end of 2014, the total assets under management by the U.S. mutual fund industry reached \$15.9 trillion, with 43.3% of households investing in mutual funds (Investment Company Institute, 2015). Yet, there is little understanding about the structure of this industry.

From the information perspective, an asset management company in the mutual fund industry can be interpreted as a coalition of professional money managers. This view fits some important aspects of this industry (see the citations in Footnote 4). Our theory has the following implications.

4.1 Firm Size and Performance

Predictions 1 and 2 imply that a big asset management company is likely to include fund managers with the best-quality information. This implication is consistent with empirical findings by Chen et al. (2004) and Pollet and Wilson (2008). They show that mutual funds

affiliated with big asset management companies tend to outperform those affiliated with small asset management companies. Bhojraj et al. (2012) further show that mutual fund managers affiliated with big asset management companies indeed possess an information advantage over those affiliated with small asset management companies.

4.2 Technology and Firm Size

Prediction 3 implies that as information environment improves, the consolidation of the mutual fund industry will lead to the emergence of a few big asset management companies. Recent decades have seen fast growth in information technology, which improves information quality. During the same period, the mutual fund industry experienced a wave of mergers, which gave rise to a few gigantic firms. For example, BlackRock acquired State Street Research in 2005, Merrill Lynch Investment Managers in 2006, Quellos Group in 2007, and Barclays Global Investors in 2009. As of September 2014, Blackrock is the biggest asset management company.

4.3 The Geography

Prediction 4 implies that the mutual fund industry can have an interesting geographic patterns. Specifically, a small number of big asset management companies tend to arise in areas in which there is a large population and investors receive good-quality information. The areas in the U.S. that fit this description include Boston, Chicago, New York, Philadelphia, Los Angeles, and San Francisco.

5 Conclusions

In this article, we develop a theory of endogenous coalition formation decisions by market players to study the coalition structure in financial markets. In our model, the benefit

of forming a coalition is that the allied members gain information advantage as well as monopolistic power in trading. However, the coalition has two types of costs. First, there can be direct costs, such as costs related to search, setup, and coordination efforts. Second, there can be an indirect cost. Specifically, as the coalition gains monopolistic power and behaves more strategically, the market maker lowers market liquidity to break even. This dries up market liquidity. Such a trade-off determines the coalition structure in the economy.

Our model has several interesting results on the coalition structure. First, a coalition is likely to be formed by informed traders with the best-quality information. Second, a coalition, if formed, must be sufficiently large. Third, as the advance of information technology expedites information processing and dissemination, the coalition size increases and, accordingly, the number of coalitions decreases. Fourth, a small number of large coalitions are likely to emerge from the group of informed traders with good-quality information and the group of informed traders with a large population.

From the information perspective, financial intermediaries (e.g., asset management companies and brokerage houses) can be viewed as sets of coalitions endogenously chosen by market players (e.g., fund managers and financial analysts) in pursuit of information advantage and monopolistic power in trading. Our model provides novel insights about the industry structure of financial intermediaries.

Our model also predicts that networks, in the form of coalitions, have negative effects on the informativeness of stock prices and market liquidity. This prediction is different from predictions of existing theories in the literature, such as Colla and Mele (2010) and Ozsoylev and Walden (2011).

References

- [1] Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi, 2013, Systemic risk and stability in financial networks, Working Paper.
- [2] Allen, F., and A. Babus, 2009, Networks in finance, in P. Kleindorfer and J. Wind (eds.), *Network-based Strategies and Competencies*, 367-382.
- [3] Allen, F., A. Babus, and E. Carletti, 2012, Asset commonality, debt maturity and systemic risk, *Journal of Financial Economics* 104, 519-534.
- [4] Babus, A., 2013, The formation of financial networks, Working Paper.
- [5] Back, K., H. H. Cao, and G. A. Willard, 2000, Imperfect competition among informed traders, *Journal of Finance* 55, 2117-2155.
- [6] Bala, V., and S. Goyal, 2000, A noncooperative model of network formation. *Econometrica* 68, 1181-1229.
- Insiders, gurus, and credibility, *Quarterly Journal of Economics* 107, 921-958.
- [7] Bhattacharya, U., J. H. Lee, and V. K. Pool, 2013, Conflicting family values in mutual fund families, *Journal of Finance* 68, 173-200.
- [8] Bhojraj, S., Y. J. Cho, and N. Yehuda, 2012, Mutual fund family size and mutual fund performance: The role of regulatory changes, *Journal of Accounting Research* 50, 647-684.
- [9] Bluhm, M., E. Faia, and J. P. Krahnen, 2013, Endogenous banks' network, cascades and systemic risk, Working Paper.

- [10] Blume, L., D. Easley, J. Kleinberg, R. Kleinberg, and E. Tardos, 2011, Network formation in the presence of contagious risk, in Proceedings of the 12th ACM conference on Electronic commerce, 1-10.
- [11] Cabrales, A., P. Gottardi, and F. Vega-Redondo, 2012, Risk-sharing and contagion in networks, Working Paper.
- [12] Cao, H. H., and D. Ye, 2014, Social network, herding and competition, Working Paper.
- [13] Chen, J., H. Hong, M. Huang, and J. D. Kubik, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review* 90, 1276-1302.
- [14] Cohen, L., A. Frazzini, and C. Malloy, 2008, The small world of investing: Board connections and mutual fund returns, *Journal of Political Economy* 116, 951-979.
- [15] Colla, P., and A. Mele, 2010, Information linkages and correlated trading, *Review of Financial Studies* 23, 203-246.
- [16] Dessein, W., and T. Santos, 2006, Adaptive organizations, *Journal of Political Economy* 114, 956-995.
- [17] Dybvig, P., H. Farnsworth, and J. Carpenter, 2010, Portfolio performance and agency, *Review of Financial Studies* 23, 1-23.
- [18] Elton, E. J., M. J. Gruber, and T. C. Green, 2007, The impact of mutual fund family membership on investor risk, *Journal of Financial and Quantitative Analysis* 42, 257-277.
- [19] Farboodi, M., 2015, Intermediation and voluntary exposure to counterparty risk, Working Paper.

- [20] Foster, F. D., and S. Viswanathan, 1996, Strategic trading when agents forecast the forecasts of others, *Journal of Finance* 51, 1437-1478.
- [21] Gaspar, J., M. Massa, and P. Matos, 2006, Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization, *Journal of Finance* 61, 73-104.
- [22] Grinblatt, M., and M. Keloharju, 2001, How distance, language, and culture influence stockholdings and trades, *Journal of Finance* 56, 1053-1073.
- [23] Gervais, S., A. Lynch, and D. Musto, 2005, Fund families as delegated monitors of money managers, *Review of Financial Studies* 18, 1139-1169.
- [24] Han, B., and L. Yang, 2013, Social networks, information acquisition, and asset prices, *Management Science* 59, 1444-1457.
- [25] He, Z., and W. Xiong, 2013, Delegated asset management, investment mandates, and capital immobility, *Journal of Financial Economics* 107, 239-258.
- [26] Hojman, D. A., and A. Szeidl, 2006, Endogenous networks, social games, and evolution, *Games and Economic Behavior* 55, 112-130.
- [27] Hojman, D. A., and A. Szeidl, 2008, Core and periphery in networks, *Journal of Economic Theory* 139, 295-309.
- [28] Holden, C. W., and A. Subrahmanyam, 1992, Long-lived private information and imperfect competition, *Journal of Finance* 47, 247-270.
- [29] Hong, H., J. D. Kubik, and J. C. Stein, 2004, Social interaction and stock-market participation, *Journal of Finance* 49, 137-163.

- [30] Hong, H., J. D. Kubik, and J. C. Stein, 2005, Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers, *Journal of Finance* 60, 2801-2824.
- [31] Ivković, Z., and S. Weisbenner, 2007, Information diffusion effects in individual investors' common stock purchases: Covet thy neighbors' investment choices, *Review of Financial Studies* 20, 1327-1357.
- [32] Jackson, M. O., 2010, *Social and Economics Networks*, Princeton University Press, New Jersey.
- [33] Jackson, M. O., and A. Wolinsky, 1996, A strategic model of social and economic networks, *Journal of Economic Theory* 71, 44-74.
- [34] Kyle, A., 1985, Continuous auctions and insider trading, *Econometrica* 56, 129-176.
- [35] Nanda, V., Z. J. Wang, and L. Zheng, 2004, Family values and the star phenomenon: Strategies of mutual fund families, *Review of Financial Studies* 17, 667-698.
- [36] Ou-Yang, H., 2003, Optimal contracts in a continuous-time delegated portfolio management problem, *Review of Financial Studies* 16, 173-208.
- [37] Ozsoylev, H., and J. Walden, 2011, Asset pricing in large information networks, *Journal of Economic Theory* 146, 2252-2280.
- [38] Palomino, F., and A. Prat, 2003, Risk taking and optimal contracts for money managers, *Rand Journal of Economics* 34, 113-137.
- [39] Pollet, J. M., and M. Wilson, 2008, How does size affect mutual fund behavior? *Journal of Finance* 63, 2941-2969.

- [40] Shapley, L. S., 1953, A value for n -person games, *Annals of Mathematical Studies* 28, 307-317.
- [41] Stein, J. C., 2008, Conversations among competitors, *American Economic Review* 98, 2150-2162.
- [42] Vayanos, D., and P. Woolley, 2013, An institutional theory of momentum and reversal, *Review of Financial Studies* 26, 1087-1145.
- [43] Zawadowski, A., 2013, Entangled financial systems, *Review of Financial Studies* 26, 1291-1323.

Appendix

Proof of Proposition 1: Our proof has two steps. In Step 1, we study how an informed trader chooses her demand, conditional on the price and all the other informed traders' demands being given by Proposition 1. In Step 2, we study how the market maker sets up the price, conditional on all informed investors' demands being given by Proposition 1.

Step 1: Consider an informed trader j . Suppose that the price, $P(NA)$, and the demands of all other informed investors, $D_i(NA)$, $\forall i \neq j$, are given by Proposition 1. Then, her payoff from trading can be expressed as:

$$\begin{aligned}
\Pi_j(S_j) &= E\left[D_j(\bar{F} + X - P(NA))|S_j\right] \\
&= E\left[D_j\left(X - \lambda(NA)(D_j + \sum_{i \neq j} D_i(NA) + Z)\right)|S_j\right] \\
&= E\left[D_j\left(1 - \lambda(NA) \sum_{i \neq j} \theta_i(NA)\right)X - \lambda(NA)D_j^2|S_j\right] \\
&= D_j\left(1 - \lambda(NA) \sum_{i \neq j} \theta_i(NA)\right)E[X|S_j] - \lambda(NA)D_j^2 \\
&= D_j\left(1 - \lambda(NA) \sum_{i \neq j} \theta_i(NA)\right)\frac{S_j}{1 + v_j} - \lambda(NA)D_j^2.
\end{aligned}$$

The first order condition implies

$$D_j(NA) = \frac{1 - \lambda(NA) \sum_{i \neq j} \theta_i(NA)}{2\lambda(NA)} \frac{S_j}{1 + v_j} = \frac{\sigma_z/K(NA)}{1 + 2v_j} S_j,$$

where the last equality follows by substituting the expressions of $\lambda(NA)$ and $\theta_i(NA)$, $\forall i \neq j$ from Proposition 1. The second order condition holds obviously. Therefore, we can write $D_j(NA) = \theta_j(NA)S_j$, where $\theta_j(NA) = \frac{\sigma_z/K(NA)}{1 + 2v_j}$.

Step 2: Consider the market maker. Suppose that the demands of all informed traders, $D_j(NA)$, $\forall j$, are given by Proposition 1. Then, the total demand can be expressed as:

$$D = \sum_j D_j(NA) + Z = \sum_j (\theta_j(NA)S_j) + Z = X \sum_j \theta_j(NA) + \sum_j (\theta_j(NA)\epsilon_j) + Z.$$

Substituting into the price equation gives

$$\begin{aligned} P &= \bar{F} + E[X|D = X \sum_j \theta_j(NA) + \sum_j (\theta_j(NA)\epsilon_j) + Z] \\ &= \bar{F} + \frac{\sum_j \theta_j(NA)}{\left(\sum_j \theta_j(NA)\right)^2 + \sum_j (\theta_j(NA)^2 v_j) + \sigma_z^2} D. \end{aligned}$$

Therefore, we can write $P(NA) = \bar{F} + \lambda(NA)D$, and

$$\begin{aligned} \lambda(NA) &= \frac{\sum_j \theta_j(NA)}{\left(\sum_j \theta_j(NA)\right)^2 + \sum_j (\theta_j(NA)^2 v_j) + \sigma_z^2} \\ &= \frac{\sum_j \frac{\sigma_z/K(NA)}{1+2v_j}}{\left(\sum_j \frac{\sigma_z/K(NA)}{1+2v_j}\right)^2 + \sum_j \left(\left(\frac{\sigma_z/K(NA)}{1+2v_j}\right)^2 v_j\right) + \sigma_z^2} \\ &= \frac{K(NA)/\sigma_z}{1 + \sum_j \frac{1}{1+2v_j}}, \end{aligned}$$

where the last equality follows by substituting into the expression of $K(NA)$.

Q.E.D.

Proof of Lemma 1: It suffices to show that the distribution of X conditional on S_j , $\forall j \in A$, is identical to the distribution of X conditional on S_A . Note that X, S_j ($\forall j \in A$),

and S_A are normally distributed. So the conditional distribution of X must be a normal distribution. We just need to show that

$$\begin{aligned} E[X|S_j, \forall j \in A] &= \frac{S_A}{1 + v_A} = E[X|S_A], \\ \text{Var}[X|S_j, \forall j \in A] &= \frac{v_A}{1 + v_A} = \text{Var}[X|S_A], \end{aligned}$$

which follows immediately after we write down the joint distribution of X, S_j ($\forall j \in A$), and S_A .

Q.E.D.

Proof of Proposition 2: Consider the coalition as a hypothetical informed trader, indicated by A , who observes a private signal S_A . The remaining proof is identical to the proof of Proposition 1.

Q.E.D.

Proof of Corollary 1: (i) It follows from Proposition 2 that

$$\begin{aligned} \text{Var}(X|P(A)) &= \text{Var}\left[X|D = D_A(A) + \sum_{j \notin A} D_j(A) + Z\right] \\ &= \text{Var}(X) - \lambda(A)\text{Cov}(X, D) \\ &= 1 - \lambda(A)\left(\theta_A(A) + \sum_{j \notin A} \theta_j(A)\right) \\ &= 1 - \frac{K(A)/\sigma_z}{1 + \frac{1}{1 + 2v_A} + \sum_{j \notin A} \frac{1}{1 + 2v_j}} \left(\frac{\sigma_z/K(A)}{1 + 2v_A} + \sum_{j \notin A} \frac{\sigma_z/K(A)}{1 + 2v_j}\right) \\ &= \frac{1}{1 + \frac{1}{1 + 2v_A} + \sum_{j \notin A} \frac{1}{1 + 2v_j}}. \end{aligned}$$

Similarly,

$$\text{Var}(X|P(A')) = \frac{1}{1 + \frac{1}{1 + 2v'_A} + \sum_{j \notin A'} \frac{1}{1 + 2v_j}}.$$

For $\text{Var}(X|P(A')) > \text{Var}(X|P(A))$, it suffices to show that

$$\begin{aligned} & \left(\frac{1}{1 + 2v_{A'}} + \sum_{j \notin A'} \frac{1}{1 + 2v_j} \right) - \left(\frac{1}{1 + 2v_A} + \sum_{j \notin A} \frac{1}{1 + 2v_j} \right) \\ &= \frac{1}{1 + 2v_{A'}} - \left(\frac{1}{1 + 2v_A} + \frac{1}{1 + 2v_b} \right) \\ &= -\frac{v_A(1 + 2v_b) + v_b(1 + 2v_A)}{(v_A + v_b + 2v_A v_b)(1 + 2v_A)(1 + 2v_b)} \\ &< 0, \end{aligned} \tag{3}$$

where the second equality follows from $v_{A'} = 1/(\frac{1}{v_A} + \frac{1}{v_b})$.

(ii) Denote $G \equiv \sum_{j \notin A'} \frac{1 + v_j}{(1 + 2v_j)^2}$ and $Q \equiv \sum_{j \notin A'} \frac{1}{1 + 2v_j}$. It is straightforward to show that $G > Q/2$.

Note that

$$\begin{aligned} \lambda(A')^2 - \lambda(A)^2 &= \frac{K(A')^2/\sigma_z^2}{(1 + \frac{1}{1 + 2v_{A'}} + Q)^2} - \frac{K(A)^2/\sigma_z^2}{(1 + \frac{1}{1 + 2v_A} + \frac{1}{1 + 2v_b} + Q)^2}, \\ &\propto \frac{\frac{1 + v_{A'}}{(1 + 2v_{A'})^2} + G}{(1 + \frac{1}{1 + 2v_{A'}} + Q)^2} - \frac{\frac{1 + v_A}{(1 + 2v_A)^2} + \frac{1 + v_b}{(1 + 2v_b)^2} + G}{(1 + \frac{1}{1 + 2v_A} + \frac{1}{1 + 2v_b} + Q)^2} \\ &> \frac{\frac{1 + v_{A'}}{(1 + 2v_{A'})^2} + Q/2}{(1 + \frac{1}{1 + 2v_{A'}} + Q)^2} - \frac{\frac{1 + v_A}{(1 + 2v_A)^2} + \frac{1 + v_b}{(1 + 2v_b)^2} + Q/2}{(1 + \frac{1}{1 + 2v_A} + \frac{1}{1 + 2v_b} + Q)^2}, \end{aligned}$$

where the inequality follows from $G > Q/2$ and Eq. (3).

For $\lambda(A') > \lambda(A)$, it suffices to show that

$$\begin{aligned}\eta &\equiv \left[\frac{1+v_{A'}}{(1+2v_{A'})^2} + Q/2 \right] \left(1 + \frac{1}{1+2v_A} + \frac{1}{1+2v_b} + Q \right)^2 \\ &\quad - \left[\frac{1+v_A}{(1+2v_A)^2} + \frac{1+v_b}{(1+2v_b)^2} + Q/2 \right] \left(1 + \frac{1}{1+2v_{A'}} + Q \right)^2 \\ &> 0.\end{aligned}$$

After substituting the expression of $v_{A'} = 1 / (\frac{1}{v_A} + \frac{1}{v_b})$, write

$$\eta = \eta_1 + 2Q\eta_2 + Q^2\eta_3,$$

where

$$\begin{aligned}\eta_1 &\propto (v_A + v_b + v_A v_b) \left[4(v_b + 1)v_A^2 + (4v_b^2 + 1)v_A + 4v_b^2 + v_b \right], \\ \eta_2 &\propto (16v_b^3 + 24v_b^2 + 10v_b + 2)v_A^3 + (24v_b^3 + 20v_b^2 + 4v_b + \frac{1}{4})v_A^2 \\ &\quad + (10v_b^3 + 4v_b^2 + \frac{1}{2}v_b)v_A + 2v_b^3 + \frac{1}{4}v_b^2, \\ \eta_3 &\propto (32v_b^3 + 28v_b^2 + 8v_b + 1)v_A^3 + (28v_b^3 + 16v_b^2 + 2v_b)v_A^2 + (8v_b^3 + 2v_b^2)v_A + v_b^3.\end{aligned}$$

It is obvious that $\eta_1, \eta_2, \eta_3 > 0$. Therefore, $\eta > 0$ and $\lambda(A') > \lambda(A)$.

(iii) Note that $\forall \alpha, \beta > 0$. We have the following inequality:

$$\begin{aligned}f(\alpha, \beta) &\equiv \beta(\alpha + \beta + \alpha\beta)(1 + 2\alpha)^2 - (1 + \alpha)(\alpha + \beta + 2\alpha\beta)^2 \\ &= -\alpha^3(4 + 3\beta) - \alpha^2(1 + 5\beta) - \alpha\beta \\ &< 0.\end{aligned}$$

Substituting $v_{A'} = 1 / (\frac{1}{v_A} + \frac{1}{v_b})$ yields

$$\begin{aligned} K(A')^2 - K(A)^2 &= \frac{1 + v_{A'}}{(1 + 2v_{A'})^2} - \frac{1 + v_A}{(1 + 2v_A)^2} - \frac{1 + v_b}{(1 + 2v_b)^2} \\ &\propto f(v_A, v_b)(1 + 2v_A)^2 + f(v_b, v_A)(1 + 2v_b)^2 \\ &< 0. \end{aligned}$$

It follows from $K(A') < K(A)$ that $\forall j \notin A'$,

$$\theta_j(A') = \frac{\sigma_z / K(A')}{1 + 2v_j} > \frac{\sigma_z / K(A)}{1 + 2v_j} = \theta_j(A).$$

It follows from $K(A') < K(A)$ and $v_{A'} < v_A$ that

$$\theta_{A'}(A') = \frac{\sigma_z / K(A')}{1 + 2v_{A'}} > \frac{\sigma_z / K(A)}{1 + 2v_A} = \theta_A(A).$$

Q.E.D.

Proof of Corollary 2: (i) It follows from $\theta_j(A) > \theta_j(NA)$ and $\lambda(A) > \lambda(NA)$ (see Corollary 1) that

$$\Gamma_j(A) = E\Pi_j(A) - E\Pi_j(NA) = \lambda(A)\theta_j^2(A)(1 + v_j) - \lambda(NA)\theta_j^2(NA)(1 + v_j) > 0.$$

(ii) It follows from $\lambda(A) > \lambda(NA)$ (see Corollary 1) that

$$\Gamma_L(A) = E\Pi_L(A) - E\Pi_L(NA) = (\lambda(NA) - \lambda(A)) \cdot \sigma_z^2 < 0.$$

Q.E.D.

Proof of Corollary 3: (i) Denote $v_{23} = 1 / (\frac{1}{v_2} + \frac{1}{v_3})$. Write

$$\begin{aligned}
& \Gamma_A(A = \{2, 3\}) \\
&= E\Pi_A(A = \{2, 3\}) - [E\Pi_2(NA) + E\Pi_3(NA)] \\
&= \frac{\sigma_z}{\sqrt{\frac{1+v_{23}}{(1+2v_{23})^2} + \frac{1+v_1}{(1+2v_1)^2}}} \frac{\frac{1+v_{23}}{(1+2v_{23})^2}}{1 + \frac{1}{1+2v_{23}} + \frac{1}{1+2v_1}} \\
&\quad - \frac{\sigma_z}{\sqrt{\frac{1+v_1}{(1+2v_1)^2} + \frac{1+v_2}{(1+2v_2)^2} + \frac{1+v_3}{(1+2v_3)^2}}} \frac{\frac{1+v_2}{(1+2v_2)^2} + \frac{1+v_3}{(1+2v_3)^2}}{1 + \frac{1}{1+2v_1} + \frac{1}{1+2v_2} + \frac{1}{1+2v_3}}.
\end{aligned}$$

Denote $v_2 = v_1 + a$ and $v_3 = v_1 + b$ where $b \geq a \geq 0$. We can show that $\Gamma_A(A = \{2, 3\})$ is proportional to a polynomial of v_1 , a , and b , which is non-positive. (We derive this polynomial using Mathematica. It is six pages long and available upon request from the authors.) Therefore, $\Gamma_A(A = \{2, 3\}) \leq 0$.

(ii) Denote $v_{12} = 1 / (\frac{1}{v_1} + \frac{1}{v_2})$, and $v_{13} = 1 / (\frac{1}{v_1} + \frac{1}{v_3})$. Write

$$\begin{aligned}
& \Gamma_A(A = \{1, 2\}) \\
&= E\Pi_A(A = \{1, 2\}) - [E\Pi_1(NA) + E\Pi_2(NA)] \\
&= \frac{\sigma_z}{\sqrt{\frac{1+v_{12}}{(1+2v_{12})^2} + \frac{1+v_3}{(1+2v_3)^2}}} \frac{\frac{1+v_{12}}{(1+2v_{12})^2}}{1 + \frac{1}{1+2v_{12}} + \frac{1}{1+2v_3}} \\
&\quad - \frac{\sigma_z}{\sqrt{\frac{1+v_1}{(1+2v_1)^2} + \frac{1+v_2}{(1+2v_2)^2} + \frac{1+v_3}{(1+2v_3)^2}}} \frac{\frac{1+v_1}{(1+2v_1)^2} + \frac{1+v_2}{(1+2v_2)^2}}{1 + \frac{1}{1+2v_1} + \frac{1}{1+2v_2} + \frac{1}{1+2v_3}},
\end{aligned}$$

and

$$\begin{aligned}
& \Gamma_A(A = \{1, 3\}) \\
&= E\Pi_A(A = \{1, 3\}) - [E\Pi_1(NA) + E\Pi_3(NA)] \\
&= \frac{\sigma_z}{\sqrt{\frac{1+v_{13}}{(1+2v_{13})^2} + \frac{1+v_2}{(1+2v_2)^2}}} \frac{\frac{1+v_{13}}{(1+2v_{13})^2}}{1 + \frac{1}{1+2v_{13}} + \frac{1}{1+2v_2}} \\
&\quad - \frac{\sigma_z}{\sqrt{\frac{1+v_1}{(1+2v_1)^2} + \frac{1+v_2}{(1+2v_2)^2} + \frac{1+v_3}{(1+2v_3)^2}}} \frac{\frac{1+v_1}{(1+2v_1)^2} + \frac{1+v_3}{(1+2v_3)^2}}{1 + \frac{1}{1+2v_1} + \frac{1}{1+2v_2} + \frac{1}{1+2v_3}}.
\end{aligned}$$

We can show using Mathematica Symbolic Computing that $\Gamma_A(A = \{1, 2\}) \geq \Gamma_A(A = \{1, 3\})$.

(iii) Similarly to the proof for Part (ii), we can also show using Mathematica Symbolic Computing that

$$\begin{aligned}
\Gamma_1(A = \{1, 2\}) &\equiv \frac{1/v_1}{1/v_1 + 1/v_2} \Gamma_A(A = \{1, 2\}) \\
&\geq \Gamma_1(A = \{1, 3\}) \equiv \frac{1/v_1}{1/v_1 + 1/v_3} \Gamma_A(A = \{1, 3\}).
\end{aligned}$$

Q.E.D.

Figure 1: A Partial Coalition When $J = 3$

There are $J = 3$ informed traders. Their information qualities satisfy $1 = v_1 \leq v_2 \leq v_3 \leq 40$. In the shaded area,

$$\Gamma_A(A = \{1, 2\}) \geq \max(0, \Gamma_A(A = \{1, 3\}), \Gamma_A(A = \{2, 3\})),$$

so a partial coalition, $A = \{1, 2\}$, is admissible.

Figure 2: A Partial Coalition When $J = 3$: Stability

There are $J = 3$ informed traders. Their information qualities satisfy $1 = v_1 \leq v_2 \leq v_3 \leq 40$. The shaded area satisfies

$$\Gamma_A(A = \{1, 2\}) \geq \max(0, \Gamma_A(A = \{1, 3\}), \Gamma_A(A = \{2, 3\})).$$

The dark-shaded area further satisfies

$$\Gamma_2(A = \{1, 2\}) = \frac{1/v_2}{1/v_1 + 1/v_2} \Gamma_A(A = \{1, 2\}) \geq \Gamma_2(A = \{1, 3\}).$$

A partial coalition, $A = \{1, 2\}$, is stable in the dark-shaded area, but fragile in the light-shaded area.

Figure 3: A Partial Coalition When $J = 10$: Case 1

There are $J = 10$ informed traders. Their information qualities satisfy $1 = v_1 \leq v_2 \leq v_3 \leq 20$ and $v_j = 50, \forall j > 3$. In the shaded area,

$$\Gamma_A(A = \{1, 2\}) \geq \max(0, \Gamma_A(A = \{1, 3\}), \Gamma_A(A = \{2, 3\})),$$

so a partial coalition, $A = \{1, 2\}$, is admissible.

Figure 4: A Partial Coalition When $J = 10$: Case 2

There are $J = 10$ informed traders. Their information qualities satisfy $1 = v_1 \leq v_2 \leq v_3 \leq 20$ and $v_j = 35$, $\forall j > 3$. In the shaded area,

$$\Gamma_A(A = \{1, 2\}) \geq \max(0, \Gamma_A(A = \{1, 3\}), \Gamma_A(A = \{2, 3\})),$$

so a partial coalition, $A = \{1, 2\}$, is admissible.

(a): The synergy of Hypothetical Partial Coalition $A = \{1, 2\}$, $\Gamma_A(A = \{1, 2\})$

(b) Profit Change of an Independent Informed Trader, $\Gamma_j(A = \{1, 2\})$, $\forall j \geq 3$

Figure 5: Welfare Effects of Hypothetical Partial Coalition

There are $J = 10$ informed traders, each of whom has the same-quality information, $v_j = V$, $\forall j$. Let $\sigma_z^2 = 100$. Panel (a) plots the synergy for a hypothetical partial coalition $A = \{1, 2\}$, $\Gamma_A(A = \{1, 2\})$, depending on V . Panel (b) plots the profit change of an independent informed trader due to the coalition, $\Gamma_j(A = \{1, 2\})$, $\forall j \geq 3$, depending on V .

Figure 6: Minimum Coalition Size: Case 1

There are $J = 40$ informed traders, each of whom has the same-quality information, $v_j = V, \forall j$. We assume that there can be 1, 2, or 3 coalitions. Because of symmetry, each coalition has the same number of informed players. The minimum size of an admissible coalition, $\underline{m}$, is given by:

$$\begin{aligned} \min_m \quad & m \\ \text{s.t.} \quad & \Gamma_A(A = \{1, 2, \dots, m\}) \geq 0. \end{aligned}$$

This figure plots the minimum coalition size, $\underline{m}$, depending on V .

Figure 7: Minimum Coalition Size: Case 2

There can be $J = 20, 30$, or 40 informed traders, each of whom has the same-quality information, $v_j = 2.5, \forall j$. We assume that there can be several coalitions. Because of symmetry, each coalition has the same number of informed players. The minimum size of an admissible coalition, $\underline{m}$, is given by:

$$\begin{aligned} \min_m \quad & m \\ \text{s.t.} \quad & \Gamma_A(A = \{1, 2, \dots, m\}) \geq 0. \end{aligned}$$

This figure plots the minimum coalition size, $\underline{m}$, depending on the number of coalitions.

(a) Optimal Coalition Size

(b) Optimal Number of Coalitions

Figure 8: Optimal Coalition Structure

There can be $J = 30$ or 40 informed traders, each of whom has the same-quality information, $v_j = V$, $\forall j$. By symmetry, there can be n coalitions, each of which has m informed traders. The optimal $\{m, n\}$ are given by:

$$\max_{m,n} \frac{1}{m} [\Gamma_A(A = \{1, 2, \dots, m\}) - C(A(m))],$$

where $C(A(m)) = 10^{-4}(m-1)^2$. This figure plots the optimal $\{m, n\}$ depending on V .

(a) Optimal Coalition Size

(b) Optimal Number of Coalitions

Figure 9: Optimal Coalition Structure with Two Isolated Groups of Informed Traders: Case 1

There are two isolated groups. Each group has 40 informed traders with the same-quality information, represented by V_1 and V_2 . Let $V_1 = 1$ and $V_2 > 1$. By symmetry, in group 1 (2), there can be n_1 (n_2) coalitions, each of which has m_1 (m_2) informed traders. The optimal $\{m_1, m_2, n_1, n_2\}$ are given by:

$$\max_{m_1, m_2, n_1, n_2} \frac{1}{m_1} \left[\Gamma_A(A = \{1, \dots, m_1\}) - C(A(m_1)) \right] + \frac{1}{m_2} \left[\Gamma_A(A = \{1, \dots, m_2\}) - C(A(m_2)) \right],$$

where $C(A(m)) = 10^{-4}(m-1)^2$. This figure plots the optimal $\{m_1, m_2, n_1, n_2\}$ depending on V_2 .

(a) Optimal Coalition Size

(b) Optimal Number of Coalitions

Figure 10: Optimal Coalition Structure with Two Isolated Groups of Informed Traders: Case 2

There are two isolated groups. Group 1 (2) has J_1 (J_2) informed traders. Let $J_1 > 100$ and $J_2 = 100$. Informed traders in both groups have the same-quality information, $V_1 = V_2 = 5$. By symmetry, in group 1 (2), there can be n_1 (n_2) coalitions, each of which has m_1 (m_2) informed traders. The optimal $\{m_1, m_2, n_1, n_2\}$ are given by:

$$\max_{m_1, m_2, n_1, n_2} \frac{1}{m_1} [\Gamma_A(A = \{1, \dots, m_1\}) - C(A(m_1))] + \frac{1}{m_2} [\Gamma_A(A = \{1, \dots, m_2\}) - C(A(m_2))],$$

where $C(A(m)) = 10^{-5}(m-1)^2$. This figure plots the optimal $\{m_1, m_2, n_1, n_2\}$ depending on J_1 .

Essay Two: Covenant Violation and Strategic Alliances

Abstract

This study examines the influence of covenant violations on violation firms' alliance activities. We find that firms witness a decline in the number of strategic alliances (especially joint ventures) in the years following debt covenant violations. The causality is established through difference-in-difference regressions and the regression discontinuity design. Our findings support the argument that covenant violation can be detrimental to a firm's reputation, deterring potential partner firms from forming alliances with violation firms. This study contributes to covenant violation research by highlighting the ramifications of reputation damage triggered by covenant violation on corporate alliance activities.

Keywords: Covenant Violation; Strategic Alliances; Joint Ventures; Regression Discontinuity Design

JEL classification: G21; G23; G32; G34

1. Introduction

Debt governance research has shown that debt covenant violation, practically transferring control rights to creditors, can place constraints on managerial discretion over important corporate decisions (Chava and Roberts, 2008; Nini, Smith and Sufi, 2012; Roberts and Sufi, 2009). Chava and Roberts (2008) find that a financial covenant violation can give rise to a decline in capital investment intensity. Findings by Nini et al. (2012) suggest that firms having violated debt covenants witness a decrease in acquisition intensity and shareholder payouts but an increase in CEO turnover likelihood. To date, covenant violation research has focused on how covenant violation shapes focal firms' investment decisions and governance quality without considering the broader ramifications of covenant violation.

To answer this question, this study examines the influence of debt covenant violation on firms' alliance activities. We raise two completing hypotheses about the relationship between debt covenant violation and firm alliance activities. On the one hand, debt governance research suggests that covenant violation firms experience an improvement in their governance quality subsequent to covenant violation (Chava and Roberts, 2008; Nini *et al.*, 2012; Roberts and Sufi, 2009). Meanwhile, findings by Bodnaruk, Massa and Simonov (2013) suggest that a firm's quality of governance is positively associated with its alliance activities because well-governed firms mitigates agency issues between alliance partners. In this sense, violation firms should experience an increase in the number of alliances in the post-violation period.

On the other hand, debt covenant violation can be detrimental a firm's reputation of being a "trustworthy" partner and deter potential alliance partners from forming alliances with violation firms. A firm's reputation offers valuable information about the firm and plays a

critical role in shaping investors' decisions (Beatty and Ritter, 1986; Demiroglu and James, 2010; Grenadier, Malenko and Strebulaev, 2014; Nahata, 2008). For instance, venture capital (VC) firm reputation is valuable not only to VCs and their investors but also to potential portfolio firms that rely heavily on VC advisory services and risk capital (Krishnan *et al.*, 2011). We posit that debt covenant violation can adversely influence a firm's reputation of being a "trustworthy" partner, deterring potential alliance partners from forming alliances with violation firms. In this sense, violation firms should experience a drop in the number of alliances from the pre-violation period to the post-violation period.

Using a sample of more than 8,199 financial covenant violations, we find that firms experience a sharp decline (13%) in the number of alliances formed from the pre-violation period to the post-violation period. To establish causality between covenant violation and alliance activity decline, we use difference-in-difference (DID) regressions and the regression discontinuity design (RDD). The DID approach compares the alliance formation of violating firms with otherwise comparable non-violating firms. We first use propensity score matching to match each violating firm (treatment) with a non-violating firm (control). We then test the differences in the change of the number of alliances formed by the violating and non-violating firms. We find that the change in the number of alliances for violation firms is 54.84% larger than that for the comparable non-violating firms.

We follow Chava and Roberts (2008) to conduct RDD analyses. Essentially, RDD compares firms that just violate covenants to those barely meet the thresholds. Since RDD relies on locally exogenous variation in covenant violation status generated by the distance to covenant threshold, the violation is very close to an independent and random variable when we use a narrow band. Hence, RDD is a very powerful test that rules out the effect of unobservable firm

characteristics. We find a 20.56% decrease in the number of joint ventures (JVs) following covenant violation, but only find weak evidence from the decrease in the number of alliances. We attribute the difference to the fact that JVs are independent legal entities that require higher capital investments from alliance partners. Given high capital investments associated with JVs, have violated debt covenants.

However, the decrease in violation firms' alliance activities can be driven by these firms' attenuating need to ally instead of potential partner firms' reputation concerns. To rule out this alternative explanation, we conduct several analyses. First, we examine whether firms that violated debt covenants experience positive abnormal returns upon alliance announcements. We do find that alliance announcement returns are high for the violation firms, indicating that violation firms should benefit from alliances. Thus, in the post-violation period, violation firms are unlikely to be opposed to alliances; instead, alliances can facilitate access to financing and resources (Berg and Friedman, 1981; Hennart, 1988); in this sense, violation firms should have a stronger motivation to form alliances in the post-violation period.

Second, we test how a firm's reputation affects the relationship between covenant violation and alliance formation. For a firm with higher reputation, the event of covenant violation should be more surprising and hence a more negative shock. We therefore hypothesize that firms with higher reputation suffers from a larger reduction in alliance formation following covenant violation. We find the interaction terms between covenant violation and reputation proxies are all significantly negative, suggesting that the firms with higher reputation suffer from a larger reduction following the violation. For example, firms that are relatively larger experience an additional 0.059 reduction in alliances and JVs. The results provide direct evidence to our story that the channel covenant violation reduces the alliance formation is

through the detrimental effect on reputation. The attenuating need story, on the other hand, can't explain the results.

Third, we investigate whether the negative implications associated with covenant violation can spill over to alliance partners. If firms experience lower stock market returns by allying with violating firms than by allying with non-violating firms, this would provide further evidence that allying with firms that have violated covenant may not be in the interests of potential partner firms. We find that compared to allying with non-violating partners, a firm's cumulative abnormal returns (CARs) around alliance announcements is 0.80 percentage point lower allying with a firm that recently violated covenants. Relatedly, we examine whether firms that are most susceptible to alliance failures experience a negative market reaction when their alliance partners violate debt covenants. We focus on firms whose size are small relative to alliance partners and which have high R&D intensity and face financial constraints. The means of CARs are significantly negative across all these firms. For example, on average, the relatively small firms experience a significantly negative CAR of -0.268% when their partners violate covenants.

This study can potentially make two contributions. First, this study extends debt covenant violation by examining the influence of debt covenant violation on firm alliance activities. Prior studies have focused on how direct intervention by debt holders shape firm investment decisions and governance quality. Our findings imply that covenant violation can tarnish a firm's reputation and deter potential partner firms from forming alliances with violation firms, providing new insights into the implications of debt covenant violation.

Second, this study can contribute to strategic alliance research. We identify debt covenant violation as an antecedent to strategic alliance activities. Bodnaruk *et al.* (2013) find that corporate governance quality can influence firms' propensities for strategic alliances (Bodnaruk *et al.*, 2013). Our findings indicate that debt covenant violations lead potential partner firms to question whether violation firms can be trustworthy partners, leading to fewer alliances formed by violation firms. Boone and Ivanov (2012) find that a party to a strategic alliances or a JV suffers from spillover effects when the other partner files for bankruptcy. Our findings extend such findings by showing that debt covenant violation can have negative spillover effects on alliance partners.

The rest of the paper is organized as follows. Section 2 discusses related literature. Section 3 describes the data selection and variable construction. Section 4 presents the effects of covenant violation on alliance formation and addresses endogeneity problems. Section 5 adds additional analyses to support our reputation tarnish story. Section 6 concludes the paper.

2. Background and Motivation

2.1. Covenant Violation Research

Existing research has documented significant costs associated with debt covenant violation. For example, Beneish and Press (1993) show that covenant violation leads to three types of costs: (i) renegotiation costs as additional covenants need to be written, (ii) refinancing costs like increased interest rate, (iii) restructuring cost associated with changing capital structure. Furthermore, Beneish and Press (1995) provide more direct evidence about consequences of covenant violation by showing negative stock market reactions associated with violation

announcement and post-violation changes in covenants. Roberts and Sufi (2009) find that net debt issuing is sharply reduced and the terms offered by existing creditors are less favorable following covenant violation. Findings from these studies offer direct evidence that violation firms need to bear significant costs from covenant violation.

Another strand of research suggests that the bank intervention following covenant violation mitigates agency and information asymmetry problems, which can increase firm value. Chava and Roberts (2008) document a decline in corporate investment after covenant violation, particularly for firms with severe agency and information asymmetry problems. Consequently, the bank intervention following violation mitigates investment distortion. Nini *et al.* (2012) show that bank intervention can improve corporate governance as violation firms experience a decline in acquisition and capital expenditures, a reduction in leverage and payouts, and an increase in CEO turnover. They also find that firms' operating and stock price performances improve subsequent to bank intervention.

To date, existing research has focused on the direct influence of debt covenant violation on violation firms (e.g., increasing financing costs and improved governance quality). Yet, little attention has been paid to investigating the broader implications of reputation damage triggered by debt covenant violation.

2.2. Strategic Alliance Research

Strategic alliances are voluntary interfirm cooperative agreements. Alliances can be broadly categorized into equity alliances (i.e., joint ventures) and non-equity alliances. A joint venture (JV) involves the creation of a new and independent jointly owned entity whereas a non-

equity alliance does not involve the sharing or exchange of equity and can be in the form of unidirectional agreements, such as licensing, second sourcing, and distribution agreements, and bidirectional agreements such as joint contracts and technology exchange agreements (Gulati, 1995). Scholars have developed different theoretical arguments regarding the benefits of strategic alliances. Berg and Friedman (1981) argue that firms can acquire knowledge and learn from others through JVs. Stuckey (1983) and Hennart (1988) show that JVs can help firms improve efficiencies, lower transaction costs, and diversify risks. Berg and Friedman (1981) and Hennart (1988) find that JVs provide access to financing and help firms obtain needed resources.

Empirical evidence also suggests that firms can improve their performance through strategic alliances. McConnell and Nantell (1985) and Chan et al. (1997) find that firms not only witness positive alliance announcement returns but also experience an improvement in operating performance following alliance formation. Allen and Phillip (2000) show that alliance formation is positively associated with stock returns and operating performance. Krishnaswami et al. (2004) demonstrate that alliance formation causes a positive announcement return for smaller and high-growth firms, as alliances alleviate their financial constraints.

Given the aforementioned benefits associated with strategic alliances, we posit that violation firms should have a strong motivation to undertake alliances to gain access to financing and resources and to improve their performance.

2.3. Hypotheses

We raise two competing hypotheses about the relationship between debt covenant violation and firm alliance activities. On the one hand, debt governance research suggests that

bank intervention subsequent to debt covenant violation can give rise to an improvement in firms' governance quality (Nini *et al.*, 2012). Bodnaruk *et al.* (2013) argue that firms with high quality of governance are more attractive alliance partners because governance mitigates agency issues between alliance partners. In this sense, violation firms should experience an increase in the number of alliances subsequent to covenant violation assuming that bank intervention can enhance firm governance quality.

On the other hand, as violation firms fail to fulfil their contractual obligations with creditors, this may be detrimental to these firms' reputation of being a trustworthy partner. Inter-organizational trust is a key determinant to alliance formation (Gulati, 1995). Inter-organizational trust refers to the extent of trust placed in the partner firm by a focal firm (Zaheer, McEvily and Perrone, 1998). When two firms exhibit high inter-organizational trust, the likelihood of alliance formation will increase (Zaheer *et al.*, 1998) because trustable partners are anticipated to fulfill obligations and are less likely to behave opportunistically. Although trust can be cultivated through prior exchange relationships, a firm can infer whether a potential partner is trustable by the latter's other activities. The violation of debt covenants signals that a firm fails to fulfill its obligation, which will be detrimental to its organizational trust with other firms. Therefore, the reputation caused by covenant violation will reduce the number of alliances among violation firms.

3. Data Description and Sample Selection

We start with the covenant violation data from 1996 to 2011, which is collected by Nini et al. (2012) from 10-K and 10-Q SEC quarterly filings.¹ We rely on the data to inform whether a firm is in covenant violation. For details of covenant, we obtain the data from Dealscan.

Our data on alliances come from the Securities Data Company (SDC) Platinum JointVentures/Alliance database. We include both strategic alliances and joint ventures in the sample. Following Li et al. (2015), a deal is only included if: (1) the deal involves at least one US public firm; and (2) the US public firm is outside of financial industry (sic out of 6000-6999). We end up with 27761 alliances from 1993 to 2014.

We then merge the data with Compustat and CRSP to add partners' characteristics and stock returns. The final sample consists of 70,609 firm-observations from 10049 firms. We control for a set of variables that are strong predictors of debt covenant violations, following Sufi (2009) and Nini et al. (2012): $\Delta Leverage/Assets$, change in the ratio of book value of total debt divided by total assets; ΔROA , change in the ratio of operating cash flow to total assets; $\Delta Net\ worth/Assets$, change in the net worth to total assets; $\Delta Current\ Ratio$, change in the current ratio; $\Delta Interest/Assets$, change in interest expense to total assets. We also include $\Delta Tobin's\ Q$, the change in Tobin's Q from the previous year, following Gu et al. (2014).

In addition, we control for other firm and industry characteristics that might affect a firm's alliance formation. The control variables include: firm size, $Ln(AT)$, the natural logarithm of total assets; $PPE/Assets$, the R&D expenditure divided by total assets; $CAPEX/Assets$, the capital expenditure divided by total assets; HI , the Herfindahl index based on annual sales; firm

¹ The dataset is updated by Professor Amir Sufi and is available at his website <http://faculty.chicagobooth.edu/amir.sufi/index.html>. Detail of the data collection process is described in Nini, Smith, and Sufi (2012).

age, $\ln(Age)$, the natural logarithm of one plus the number of years the firm is included in Compustat; Institutional ownership, $INST$, the arithmetic mean of the four quarterly institutional holdings.

Table 1 summarizes the sample. On average, each firm forms 0.17 alliances, while the majority of firms do not form alliances. In our sample, about 7% of firm-year observations are in violation of debt covenants, which suggests that covenant violation is a fairly common event.

[Table 1 about here]

We report the correlation of variables used in our test in Table 2. The correlation between *Violation* and the three variables measuring the number of alliances: ($\ln(1 + Alliance\&JV)$, $\ln(1 + JV)$ and $\ln(1 + Alliances)$) are all highly significantly negative, which is consistent with our first hypothesis that covenant violation reduces alliance formation.

[Table 2 about here]

4. Covenant Violation and Alliances Formation

4.1 Raw patterns on Alliance Formation Surrounding Covenant Violations

We first describe the raw pattern of alliance formation surrounding covenant violations to see whether there is a time trend. Specifically, for each violating firm, we retain the number of alliances formed for a seven-year window centred at the violation year. We then run the following pooled regression:

$$\ln(1 + Alliances\&JV / JV / Alliances)_{i,t} = \alpha + \beta_1 Before_{i,t}^{-1} + \beta_2 Current_{i,t} + \beta_3 After_{i,t}^1 + \beta_4 After_{i,t}^{2\&3} + Year_t + Industry_j + \varepsilon_{i,t}, \quad (1)$$

The dependant variable $\ln(1 + \text{Alliance\&JV})$ is defined as the natural logarithm of 1 plus the number of alliances and JV of firm i in Year t . We also use $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ as dependant variables, where the numbers of JV only or alliances only are counted respectively. $\text{Before}_{i,t}^{-1}$ is a dummy that equals 1 if the firm-year observation is in the year before the firm's violation year and 0 otherwise. $\text{Current}_{i,t}$ is a dummy equals 1 if the firm-year observation is in the year when the violation occurs and 0 otherwise. $\text{After}_{i,t}^1$ is a dummy that equals 1 if the firm-year observation is in the year after the firm's violation year and 0 otherwise. $\text{After}_{i,t}^{2\&3}$ is a dummy that equals 1 if the firm-year observation occurs two or three years after the firm's violation year and 0 otherwise. Therefore, the benchmark is the observations in two or three years before the violation year.

The results are reported in Table 3. In Panel A, we run OLS regression, while in Panel B we use Tobit regression. We use $\ln(1 + \text{Alliance\&JV})$, $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ as dependant variables in Column (1) to (3) respectively. When using OLS regression, the patterns of different types of alliances are similar: the coefficients of $\text{Before}_{i,t}^{-1}$ and $\text{Current}_{i,t}$ are not significant, suggesting that alliance formation is stable before the firm's covenant violation. However, we find the estimated coefficients of $\text{After}_{i,t}^1$ and $\text{After}_{i,t}^{2\&3}$ are significantly negative in all three columns, suggesting that there is a pattern of declining number of alliances after the firm violates covenant. Given that the average number of alliances formed is 0.19, the reduction in alliance formation is also economically significant. For example, for a firm in covenant violation, on average, its number of alliances & JV reduces by 6.5% of the average alliance numbers in the year immediately after violation, and reduces another 10% of the average number in the next two years. The pattern is similar when using Tobit regression, except that there are some evidences of upward trend of alliance formation before covenant violation.

[Table 3 about here]

4.2 Panel Data Evidence

In this section, we use formal test to study the effect of firm's covenant violation on its number of alliances formed. Specifically, we run the following pooled OLS regression²:

$$\ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t+n} = \alpha + \beta \text{Violation}_{i,t} + \gamma' \text{Controls}_{i,t} + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t}, \quad (2)$$

The sample includes all the US non-financial firms from year 1996 to 2011 regardless of whether it violates covenants. To ensure that the firms are comparable, we include only firms that have outstanding bank loans. Results are reported in Table 4. The dependant variable in Panel A is $\ln(1 + \text{Alliance\&JV})$, which is defined as the natural logarithm of 1 plus the number of alliances and JV of firm i in Year $t+n$. Columns (1) to (3) report the results of number measured in one (t+1), two (t+2) or three (t+3) years accordingly. In Panel B and Panel C, we use $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ as dependant variables, where the numbers of JV only or alliances only are counted respectively.

Following Nini et al. (2012) and Gu et al. (2014), we define the variable of interest, $\text{Violation}_{i,t}$, as a dummy that equals to 1 if a covenant violation occurs in year t for firm i and is not preceded by a violation in the previous four quarters, and 0 otherwise. The identification essentially picks only “new” violations. The control variables are discussed in Section 3.

² We also run Tobit regression for the model, the results are qualitatively similar.

The estimated coefficients of *Violation* in Panel (A) of Table 4 are all significantly negative, showing that covenant violation has a negative effect on the firm's alliance formation. For example, if a firm violates covenant in Year t , then on average, it will experience a decline in number of alliances by 0.022, which is 13% of the average number of alliances within our sample. In Panel B and Panel C, the results are similar when we focus on the number of JV only and alliances only.

[Table 4 about here]

4.3 Endogeneity

Till now we have documented a significantly negative correlation between covenant violation and alliance formation. However, it is possible that some unobservable firm characteristics are driving both covenant violation and the decline of alliance formation. In particular, it is possible that firms with low quality are more likely to be in covenant violation. While in the same time, other firms are reluctant to form alliances with low-quality firms.

To establish causality between covenant violation and alliance formation, we use two identification strategies: difference-in-difference (DID) approach and regression discontinuity design (RDD). Section 4.3.1 presents the result of DID approach and Section 4.3.2 presents the result of RDD approach.

4.3.1 The Difference-in-Difference Approach

In this section, we use DID approach. Specifically, we test whether a sample of treatment firms that are in covenant violation experience a different pattern of alliance formation surrounding violation, compared to a group of firms that are otherwise comparable. The advantages of this approach are twofold: (1) DID identification eliminates omitted trends that are causing both covenant violation and alliance formation. For example, it is possible that changes in economic condition are driving the violation, as well as the reduction in alliance formation simultaneously. Since DID approach compares the difference in changes, the omitted trend explanation is ruled out; (2) DID identification rules out the omitted constant difference in firm characteristics between the violation and none-violation firms. For example, it is likely that firms with low corporate governance are facing higher likelihood of covenant violation and reduction in alliance formation at the same time. DID approach controls for this difference by matching the treatment firms with a group of firms that are comparable.

For each nonfinancial US firm that is in new violation of debt covenants from 1996 to 2011, we match it with a nonfinancial firm that has not violated covenants in the previous year. Following previous literature, we define firms in new violation as those that violate covenant in year t , but have not been in covenant violation in the previous four quarters. The non-violating firms are restricted to those with outstanding bank loans, so that both treatment and control groups have loan contract, and are comparable.

The matching is done by propensity score matching. We first estimate a probit regression of covenant violation on a group of firm characteristics that are shown to affect violation in previous studies (Sufi (2009) and Nini et al. (2012)). The dependant variable is a dummy that equals to 1 if a firm violates covenant in year t and 0 otherwise. The control variables are similar

to those used in the previous section, and are measured at the year immediately before the violation. We also add the change in number of alliances to meet the parallel trend assumption.

$$Violation_{i,t} = \alpha + \gamma' Controls_{i,t-1} + Year_t + Industry_j + \varepsilon_{i,t}, \quad (3)$$

The results are reported in the first column of Panel A of Table 5. We then use the predicted probabilities to perform a nearest-neighbour propensity score matching. In specific, each violating firm is matched to a non-violating firm in the same industry and year with the closet propensity score. We end up with 3411 pairs of matched firms.

[Table 5 about here]

We then take steps to ensure that the firms are well matched. First, we re-run the above probit regression within the sample of matched firms. The result is reported in the second column of Table 5 Panel A. Most of the variables are no longer significant, except for *INST* and $\Delta Net\ worth/Assets$. However, the difference in *INST* between the treatment and control groups is not economically significant as shown in Panel B of Table 5, and $\Delta Net\ worth/Assets$ is only marginally significant. More important, the Pseudo- R^2 is only 0.003 now, suggesting that there is little explanation power of the model on covenant violation after the matching. Also, we note that change in number of alliances is not significant, suggesting that the trend of alliance formation between the groups are not affecting the violation result.

Second, we report the mean differences of independent variables between treatment and control groups, to make sure that the two groups are comparable. The results are reported in Table 5 Panel B. Except for *INST* and $\Delta Net\ worth/Assets$, all the variables have mean differences that are insignificant. In particular, we do not find a significant difference in alliance formation trend between the two groups, suggesting that the parallel trend assumption is met.

We now proceed to test whether the changes in number of alliances formed are different between firms that newly violate covenants and those not in covenant violation. Specifically, we compute the changes in alliance formation by taking the difference between the number of alliances over the three-year period after violation ($[+1, +3]$) and the number of alliances over the three-year period before violation ($[-3, -1]$), for treatment firms that violate covenants. Similarly, we compute the changes in alliances for control firms that are not in covenant violation. The changes are measured separately for alliance&JV, JV only and alliance only. We then test whether the changes are different between the treatment and control groups.

Table 5 Panel C reports the results. Column 1 shows that on average, the control firms experience a reduction in number of alliances formed. It is not surprising given that these firms have characteristics similar to covenant violating firms, which are perceived to be negative signals and can deter potential partners. Column 2 shows that the violating firms have a highly significant drop in number of alliances surrounding the covenant violation. For example, the total number of alliance&JV over the three year period after violation decline by 0.135, or 79.4% of the average number of alliances each firm formed. The differences in changes between the two groups (Treatment Group - Control Group) are reported in Column 3. The results show that the treatment group has a statistically significantly larger reduction in number of alliances, regardless of the alliance types. The P-values of the differences are 0.002, 0.025 and 0.004 respectively for alliance&JV, JV only and alliances only. For example, on average, the violating firms have an additional drop of 0.042 in number of alliance&JV compared to non-violating firms. This difference is also economically significant as it is 54.84% of the reduction the non-violating firms are suffering.

Next, we use the matched pairs to run a regression, to test whether covenant violation is causing the larger reduction in number of alliances. Specifically, we retain a seven-year window of observations centred at the violation year for each firm in the treatment and control groups, and run the following regression:

$$\begin{aligned} \ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t} = & \alpha + \beta_1 \text{Violation} * \text{Current}_{i,t} + \beta_2 \text{Violation} * \\ & \text{After}_{i,t} + \beta_3 \text{Violation} + \beta_4 \text{Current}_{i,t} + \beta_5 \text{After}_{i,t} + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t}, \end{aligned} \quad (4)$$

The dependant variables are $\ln(1 + \text{Alliance\&JV})$, $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ in Column (1) to (3) respectively. *Violation* is a dummy that equals to one if the firm is in treatment group and 0 if it is in control group. *Current_{i,t}* is a dummy that equals one if the observation is in the violation year and 0 otherwise. *After_{i,t}* is a dummy that equals on if the firm is in the three-year period after violation year, and 0 otherwise. So the benchmark is the three-year period before violation. We report the results in Table 5 Panel D.

The variable of interest is the interaction term $\text{Violation}_{it} * \text{After}_{it}$, which is highly significantly negative in all three columns, suggesting that compared to control firms, the violating firms encounter a reduction of alliance formation after the violation. For example, if a firm violates covenant, then its number of alliances formed over the next three years is 0.024 less than an otherwise comparable non-violating firm. These results provide evidence that covenant violation is causing the reduction of alliance formation.

4.3.2 The Regression Discontinuity Design Approach

The DID approach can't eliminate the possibility of an omitted variable that affects the violation and non-violation firms differentially, and is correlated with alliance formation. In this section, we use regression discontinuity design (RDD) approach to test the effect of covenant violation on alliance formation, following Chava and Roberts (2008). The RDD relies on locally exogenous variation in covenant violation generated by the distance to the threshold indicated in the covenants. By narrowing the bands, RDD essentially compares the alliance formation between the firms that just violate covenant and those that just meet the covenant threshold. Therefore, RDD is a powerful identification strategy as the violation is very close to an independent random event and is unlikely to be correlated with firm unobservable characteristics. While violation firms may have deteriorating financial conditions and hence potential partners are reluctant to join the alliance, the RDD results can provide direct evidence that the reduction in alliance formation is driven by the violation per se.

The sample of RDD includes all the firms which have covenants covered in Dealscan restricting the current ratio or net worth of the firm from 1996 to 2011. Following Chava and Roberts (2008), we only include firms that satisfying the two conditions: (1) the non-financial firm is covered in both Compustat and CRSP database, as well as the Dealscan database; (2) the firm has a bank loan contract restricting other current ratio or net worth. We focus on these two restrictions as they are relatively frequent in the Dealscan data (Dichev and Skinner (2002)), also these two measures are standard to calculate. The time period over which the firm is bound by the covenant is defined as from the earliest loan start date in the package to the end of the latest maturity date. Essentially, the firm is assumed to be bound by the covenant for the longest possible life of all loans in the package.

Following previous literature (Lee and Lemieux (2010), Cunat et al (2012), Bradley et al (2013)), we first estimate a polynomial model that uses the entire sample and report the result in Table 6 Panel A. Specifically, we run the following regression:

$$\begin{aligned} \ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t} = & \alpha + \beta_1 \text{Violation}_{i,t} + \beta_2 \text{Tobin's } Q_{i,t} + \beta_3 \text{ROA}_{i,t} + \\ & P_l(\text{CR}_{i,t}) + P_r(\text{CR}_{i,t}) + P_l(\text{NW}_{i,t}) + P_r(\text{NW}_{i,t}) + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t}, \end{aligned} \quad (5)$$

The dependant variables are $\ln(1 + \text{Alliance\&JV})$, $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ measured in the three-year period following the covenant violation. Their results are reported in Column (1) to (3) respectively. *Violation* is a dummy that equals 1 if a firm's current ratio or net worth falls below the corresponding covenant threshold in any quarters in a fiscal year. Two sets of polynomials are included: $P_l(\text{CR}_{i,t})$ and $P_r(\text{CR}_{i,t})$ are polynomial (2) in terms of current ratio measured from the left-hand and right-hand sides respectively. $P_l(\text{NW}_{i,t})$ and $P_r(\text{NW}_{i,t})$ are polynomial (2) in terms of net worth measured from the left-hand and right-hand sides respectively. Polynomial (2) is a polynomial of order two in terms of distance to default. Distance to default is the absolute difference between the firm's value and the corresponding threshold. If a firm does not violate covenants, we use the average distance of the four quarters to calculate Polynomial (2). If a firm violates covenants in only one quarter, we use the distance measured in the violating quarter. If a firm is in covenants violation for more than once, we use the maximum of the distance. We also control for Tobin's Q and ROA in the regression, following Chava and Roberts (2008). The RDD is more powerful when the firms are close to covenant violation, thus we report the results for samples with narrow bands around the threshold. Table 6 Panel B reports the results using the sample of narrow bands where the absolute value of the relative distance to the covenant threshold is less than or equals to 0.2.

Table 6 Panel C report the results using the sample of narrow bands where the absolute value of the relative distance to the covenant threshold is less than or equals to 0.1.

When the entire sample is used, the results in Table 6 Panel A show that the effect of *violation* is significantly negative in all the three columns, suggesting that covenant violation is causing the reduction in number of alliances, even after controlling for the exact distance to violation. The more powerful evidences are from Panel B and Panel C. In Panel B we report the result using the sample of a narrow band in which the relative distance is less than or equals to 0.2, following Chava and Roberts (2008). The evidence shows that violation is significantly negative when the dependant variable is the total number of alliance&JV or JV only, but it is not significant when we count the number of alliances only. For example, when the number of JV only is counted, a firm that is in covenant violation will experience a decline in number of JV by 0.014, or 20.56% of the average number of JV formed. However, when the number of alliances only is counted, we do not find a significant change for the violating firm. We then test whether our results are sensitive to the choice of bands. In Panel C, where we report the results using the sample of a narrower band in which the relative distance is less than or equals to 0.1. The results are similar to Panel B. Specifically, we only find a significantly negative result when the dependant variables is alliance&JV or JV only.

[Table 6 about here]

We interpret the findings in the same vein as Li et al. (2014), who find a significant relationship between technological competition and alliance formation only, but not between competition and JV formation. The difference in the results between alliance and JV lies in the fact that alliance is a flexible arrangement, while JV is a rigid legal entity that requires a high

contract cost. While the cost of setting up an alliance or JV is a sunk cost, the potential partners are more reluctant to form JV, as they are afraid that the violating firm may impair their reputation and may not be able to hold to agreements, and eventually they have to terminate the deal and suffer the sunk costs. In summary, the results of Table 6 suggest that covenant violation causes the reduction of alliance formation, particularly for JV which is associated with higher setting up cost.

The results from DID and RDD analyses deal with the endogeneity problem and confirm the causality between covenant violation and alliance formation, however, the evidences for JV formation outcomes are stronger than alliances-only outcomes.

5. Additional Analyses

Till now, we have established the causality between covenant violation and alliance formation, however, the decrease in violation firms' alliance activities can be driven by these firms' attenuating need to ally rather than potential partner firms' reputation concerns. To rule out this alternative explanation, we conduct several analyses in this section.

5.1 Attenuating need of Covenant Violating Firm

Existing literature provides evidence that alliance formation is value-enhancing, which suggests that a violating firm is unlikely to avoid forming alliances on purpose. Nevertheless, we provide some evidence in this subsection to show that the reduction in alliance formation is not driven by violating firm's attenuating need. In Panel A of Table 7, we test whether the announcement return around alliance formation is significantly positive for the violating firms. The announcement return is measured by the cumulative abnormal return adjusted by Fama-

French 3 factor model over the event windows of [-2, 1], [-3, 1], [-2, 2], [-5, 5] and [-7, 7]. We define the violating firms to be those violated covenants in the 1-year, 2-year and 3-year period before the alliance formation. The results show that the average announcement return around alliance formation is significantly positive for all the event windows and violating measures, providing strong evidence that violating firms benefit from the alliance formation.

In Panel B of Table 7, we test whether there is a difference in the reductions of R&D alliances and non-R&D alliances following the firm's covenant violation. Since alliances for R&D purpose generally take longer time to pay off, and are riskier, we hypothesize that violating firms should actively avoid such alliances first if they ever want to reduce alliance formation. Specifically, we run the following regression:

$$\begin{aligned} \ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t} = & \alpha + \beta_1 \text{Violation}_{i,t} + \beta_2 \text{R\&D Alliance}_{i,t} + \\ & \beta_3 \text{Violation}_{i,t} * \text{R\&D Alliance}_{i,t} + \gamma' \text{Firm_Controls}_{i,t-1} + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t} \end{aligned}$$

(6)

The dependant variables are $\ln(1 + \text{Alliance\&JV})$, $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ in Column (1) to (3) respectively. *Violation* is a dummy that equals 1 if the firm violated covenants in the three years preceding alliance formation, and 0 otherwise. *R&D Alliance* is a dummy that equals 1 if the firm's average R&D expenditure measured over the past five years is above the industrial median and 0 otherwise. We argue that firms with high long-term R&D expenditure are more likely to form alliances for R&D purpose. We expect the interaction term between R&D alliance and violation to be insignificant. The results in Panel B of Table 7 are consistent with our intuition. We do not find a significant difference between reduction in R&D alliance and non-R&D alliance formations for the violating firms.

5.2 Reputation and the Relation between Covenant Violation and Alliance Formation

In this section, we test how the firm's reputation affects the relationship between covenant violation and alliance formation. For a firm with higher reputation, the event of covenant violation should be more surprising and hence a more negative shock. We therefore hypothesize that firms with higher reputation suffer from a larger reduction in alliance formation following covenant violation. Specifically, we run the following regression and report the results in Table 8:

$$\begin{aligned} \ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t} = & \alpha + \beta_1 \text{Violation}_{i,t} + \beta_2 \text{ReputationProxy} + \\ & \beta_3 \text{Violation}_{i,t} * \text{ReputationProxy} + \gamma' \text{Firm_Controls}_{i,t-1} + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t} \end{aligned} \quad (7)$$

The dependant variables are $\ln(1 + \text{Alliance\&JV})$, $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ in Column (1) to (3) respectively. *Violation* is a dummy that equals 1 if the firm violated covenants in the three years preceding alliance formation, and 0 otherwise. For reputations proxies, we use two dummy variables: *Large* is a dummy that equals 1 if the firm's asset is greater than the median of the firms in the same year and industry, and 0 otherwise; *S\&P500* is a dummy that equals 1 if the firm is included in the S\&P500 index and 0 otherwise. We report the results using *Large* and *S\&P500* in Panel A and Panel B of Table 8 correspondingly.

The interaction terms between covenant violation and reputation proxies are all significantly negative, suggesting that the firms with higher reputation suffer from a larger reduction following the violation. For example, firms that are relatively larger experience an additional 0.059 reduction in alliances and JVs.

[Table 8 about here]

The results we document in this subsection provide direct evidence to our story that the channel covenant violation reduces the alliance formation is through the detrimental effect on reputation. The attenuating need story, on the other hand, can't explain the results.

5.3 Covenant Violation and Announcement Return of Alliance Formation

In this section, we test our hypothesis that there is a negative effect on the firm's announcement return around the partnership formation, if the firm's partner violated covenants recently. Specifically, we run the following regression and report the results in Table 9:

$$CAR_{i,t} = \alpha + \beta_1 Partner_Violation_{i,t} + \beta_2 Self_Violation_{i,t} + \gamma' Firm_Controls_{i,t-1} + \delta' Deal_Controls_{i,t} + Year_t + Industry_j + \varepsilon_{i,t}, \quad (8)$$

The dependant variable is $CAR_{i,t}$, which is defined as the firm's cumulative abnormal return adjusted by Fama-French 3 factors measured around the alliance formation. The event window is [-2, 1], [-3, 1], [-2, 2], [-5, 5] and [-7, 7] respectively from Column (1) to Column (5). $Partner_Violation_{it}$ is a dummy that equals one if the firm's partner was in covenant violation for at least once in the three years preceding the alliance formation and 0 otherwise. $Self_Violation_{it}$ is a dummy that equals one if the firm itself has been in covenant violation for at least once in the three years preceding the alliance formation and 0 otherwise. We have experimented with alternative measures of $Partner_Violation_{it}$ and $Self_Violation_{it}$ defined over the two or one year period preceding the alliance formation, the results are similar. The firm characteristics measured in the year preceding the alliance formation are controlled. We also

control for deal characteristics: *JV* is a dummy that equals one if the partnership is formed as JV and zero otherwise; *Relsize* is a dummy that equals one if the relative size of the firm to its partner is less than the sample median, and zero otherwise; *Horizontal* is a dummy that equals one if the firm and its partner are from the same industry and zero otherwise.

Table 9 reports the results. We find a significantly negative correlation between the firm's announcement return around alliance formation and the status of its partner's recent covenants violation, for all the event windows used. For example, when CAR is measured over the window $[-2, 2]$, a firm that forms alliances with a covenant-violating partner has an announcement return that is 0.8% lower than the one with a non-violating partner, which is statistically significant at 1% level. Compared to the mean announcement return of 1.14%, the effect of partner's violation status is also economically significant. Also, both *JV* and the interaction term *Partner-Violation*JV* are insignificant, suggesting that the relation we find between *Partner-Violation* and announcement return holds for difference types of alliances. However, we do not find a significant relation between the firm's announcement return and whether it was recently in covenant violation itself.

[Table 9 about here]

These results support our second hypothesis that the alliance's reputation is impaired if it involves a partner that was recently in covenant violation. In particular, the investors view the alliances involving a covenant-violating firm riskier and likely to generate lower outcomes, and hence expect smaller net present values. As a result, forming alliance with a violating counterparty leads to a decline in the firm's announcement return around the alliance formation. However, a firm's own covenant violation status doesn't affect its announcement return. On one

hand, if the firm itself was recently in covenant violation, we expect a higher CAR around announcement. This is because on one hand, the positive effect of being able to obtain partnership to signal financial health and growth opportunity is stronger for the violating firm than a non-violating firm. On the other hand, the firm's covenant violation per se has a negative effect due to investor's discounted value creation of the alliances. These two effects turn out to cancel each other.

We acknowledge that the magnitude of the negative spillover effects we document here are likely to be lower bounds since ex ante, firms will only accept violating partners that cause relatively minor spillover effect. In other words, we don't have any observation where the firm rejects to form alliance with a covenant violating firm, as it expects the spillover effect can outweigh any potential gain from the alliance.

5.3 Firm's Return around Its Partner's Covenant Violation Date

In this section, we test the following hypothesis: a subset of firms which are more susceptible to the alliance failures experience a negative market reaction when their partners violate covenant. When a firm's partner violates covenant, it is likely that the firm's reputation is also impaired as the investors interpret the event as a negative signal. Particularly, investors may think the firm fails to conduct thorough research and ends up with a partner that later violate covenant. In addition, the benefits of the alliances are likely to be lost if the partner is unable to hold to agreements following the covenant violation. However, this negative spillover effect is likely to be unobservable if investors don't view covenant violation as a severe event. It is also possible that the firm's reputation is not impaired if it can walk away when its partner is in

covenant violation, for example, by exercising termination rights. Therefore, we split our samples into those that are more likely to be affected by the spillover effect and those who are less likely to be affected, and test whether the findings are only significant in the former.

Specifically, we compute the CAR of the firm around its partner's covenant violation date. The CAR is adjusted by Fama-French three factors and estimated over two event windows: [-2, 1] and [-3, 1]. We do not distinguish between alliance and JV. We then compute the mean of CAR and test whether it is significant. The results are reported in Table 10.

[Table 10 about here]

Panel A reports the results using all alliance & JV. Panel B reports the mean of CAR for relatively small and large firms, and tests the mean difference of the two groups. Small firms are those with relative size (firm size/partner size) smaller than the median of firms in the same year and industry. Large firms are those with relative size larger than the median of firms in the same year and industry. We expect small firms suffer a negative stock return around their partners' covenant violations since the impact of the alliance on them are more severe given their size.

Panel C reports the mean of CAR for firms with high and low R&D, and tests the mean difference of the two groups. Firms with high R&D are those with R&D/Assets ratios higher than the median of firms in the same year and industry. Firms with low R&D are those with R&D/Assets ratios lower than the median of firms in the same year and industry. We expect firms with high R&D to suffer from negative stock return around their partners' covenant violation because these firms are more likely to have specialized assets and contractual problems in the alliance. Panel D reports the mean of CAR for constrained and liquid firms, and tests the mean difference of the two groups. Constrained firms are those with WW financial constraint

indices (Whited and Wu, 2006) higher than the median of firms in the same year and industry. Liquid firms are those with WW financial constraint indices lower than the median of firms in the same year and industry. WW index is calculated as follows:

$$WW_{i,t} = -0.091CF_{i,t} / AT_{i,t-1} - 0.062Positive_Dividend_{i,t} + 0.021*Leverage_{i,t} - 0.044Ln(AT_{i,t}) + 0.102Industry\ Sales\ Growth_{i,t} - 0.035Sales\ Growth_{i,t}, \quad (9)$$

where CF is cash flow and AT is total assets. Positive_Dividened is a dummy that equals one if the firm pays cash dividend in the year and zero otherwise. Leverage is measured as the ratio of total debts to total assets. Industry Sales Growth is the average sales growth of all firms in the firm's three-digit industry. We also experiment with HP index (Hadlock and Pierce (2010)), and the results are similar. We expect financially constrained firms to suffer from a negative stock return when their partners violate covenants. Our argument is based on the intuition that one main benefit of alliances is to alleviate financial constraints of participants, and the covenant violation of the partner raises the concern that the alliance may fail if the partner can't hold to the agreements.

In Panel A, when all the deals are included, we find an insignificantly negative stock price reaction around the partner's covenant violation date. In Panel B where we split the sample into small and large firms, we find that the small firms are associated with a significantly negative stock return around its partner's violation. For example, on average, when the CAR is measured over the window of [-2, 1], the small firms have a significantly negative return of -0.268% at 5% level. When we take the difference in stock price reaction between the small and large firms, we find that small firms' CARs are significantly lower than the large firms' CARs.

In Panel C, when we split the sample into firms with high and low R&D expenditures, we find that firms with high R&D suffer from a significantly negative stock return around their partners' covenant violation. For example, when the CAR is measured over the window $[-3, 1]$, the group of firms with high R&D has a mean CAR of -0.284% statistically significant at 5% level. The mean difference between the groups of firms with high and low R&D is also significantly negative. In Panel D, when we split the sample into financially constrained and liquid firms, we find that on average, the constrained firms are associated with significantly negative stock return around their partners' covenant violation. For example, when the CAR is measured over the $[-2, 1]$ window, the constrained firms have a mean CAR of -0.275% which is significant at 5% level. The mean difference between the constrained and liquid firms is significantly negative at 1% level. These results provide evidence that there is a spillover effect from the covenant violating firm to its non-violating partner, particularly in the subsample where the non-violating partner is likely to suffer more from the termination of alliance.

Overall, the results from Sections 5.1 and 5.2 support our hypothesis that there is a negative spillover effect within the alliances when one partner violates covenants, which in turn leads to the reluctance of firms to form alliance with covenant violating firms.

6. Conclusions

In this paper, we study the effect of covenant violation on firm's alliance formation activities. We find that if a firm violates covenants, then its number of partnerships, especially joint ventures, formed in the following years will decline. The causality is established by difference in difference analysis and regression discontinuity design approaches. The reduction

of alliances formation is due to the potential partner's reluctance to join. In particular, we document two channels through which spillover effects can transfer within alliances: the announcement return of alliance formation is reduced if the firm's counterparty violated covenant recently; a subset of non-violating firms that are more susceptible to alliance failure suffer from negative market reaction, when their counterparties violate debt covenants. These spillover effects deter the potential partners from forming alliances with the covenant violating firms, as ex ante there are additional costs. As alliance formation generally generates benefits including access to financing, our results also shed light on a new indirect detrimental effect of covenant violation on corporate finance.

References

- Allen, J., Phillips, G., 2000. Corporate equity ownership, strategic alliances, and product market relationship. *Journal of Finance* 55, 2791-2815.
- Beneish, M.D., Press, E., 1993. Costs of technical violation of accounting-based debt covenants. *The Accounting Review* 68, 233-257.
- Beneish, M.D., Press, E., 1995. The resolution of technical default. *The Accounting Review* 70, 337-353.
- Berg, S., Friedman, P., 1981. Impacts of domestic joint ventures on industrial rates of return: a pooled cross-section analysis: 1964-1975. *Review of Economics and Statistics* 63, 293-298.
- Bodnaruk, A., Massa, M., Simonov, A., 2013. Alliances and corporate governance. *Journal of Financial Economics* 107, 671-693.
- Boone, A.L., Ivanov, V.I., 2012. Bankruptcy spillover effects on strategic alliance partners. *Journal of Financial Economics* 103, 551-569.
- Bradley, D., Kim, I., Tian, X., Forthcoming. Do unions affect innovation? *Management Science*.
- Chan, S.H., Kensinger, J., Keown, A., Martin, J., 1997. Do strategic alliances create value? *Journal of Financial Economics* 46, 199-221.
- Chava, S., Roberts, M., 2008. How does financing impact investment? The role of debt covenants. *Journal of Finance* 63, 2085-2121.
- Cunat, V., Gine, M., Guadalupe, M., 2012. The vote is cast: The effect of corporate governance on shareholder value. *Journal of Finance* 67, 1943-1977.
- DeFond, M.L., and Jiambalvo J., 1994. Debt covenant violation and management of accruals. *Journal of Accounting and Economics* 17, 145-176.
- Dichev, I.D., Skinner, D.J., 2002. Large-sample of evidence on the debt covenant hypothesis. *Journal of Accounting Research* 40, 1091-1123.
- Farber, D.B., 2005. Restoring trust after fraud: Does corporate governance matter? *The Accounting Review* 80, 539-561.
- Franz, D.R., HassabElnaby, H.R., Lobo, G.J., 2014. Impact of proximity of debt covenant violation on earnings management. *Review of Accounting Studies* 19, 473-505.
- Gomes-Cassers, B. Hagedoorn, J., Jaff, A., 2006. Do alliances promote knowledge flows? *Journal of Financial Economics* 80, 5-33.
- Gu, Y., Mao, C.X., Tian, X., 2014. Bank interventions and firm innovation: Evidence form debt covenant violations. Working paper.
- Gulati, R., 1995. Does familiarity breed trust? The implication of repeated ties for contracting choice in alliances. *Academy of Management Journal* 38, 85-112.

- Hennart, J.F., 1988. A transaction costs theory of equity joint ventures. *Strategic Management Journal* 9, 361-374.
- Ivanov, V., Lewis, C., 2009. The effect of strategic alliances on initial public offerings. Unpublished working papers. U.S. Securities and Exchange Commission and Vanderbilt University.
- Johnsos, S., Houston, M., 2000. A re-examination of the motives and gains in joint ventures. *Journal of Financial and Quantitative Analysis* 35, 67-86.
- Karpoff, J.M., Lott, J.R., 1993. The reputational penalty firms bear from committing criminal fraud. *Journal of Law and Economics* 36, 757-802.
- Klein, B., Crawford, R., Alchian, A., 1978. Vertical integration, appropriable rents, and the competitive contracting process. *Journal of Law and Economics* 21, 297-326.
- Kogut, B., 1988. Joint ventures: the theoretical and empirical perspectives. *Strategic Management Journal* 9, 319-332.
- Krishnaswami, S., Pablo, E., Subramaniam, V., 2004. When is equity more than just a financing? Evidence from strategic alliances. Unpublished working paper, Tulane University.
- Lee, D., Lemieux, D., 2010. Regression discontinuity designs in economics. *Journal of Economic Literature* 48, 281-355.
- Li, K., Qiu, J., Wang, J., 2015. Technological competition and strategic alliances. Working paper.
- McConnell, J., Nantell, T., 1985. Corporate combinations and common stock returns: the case of joint venture. *Journal of Finance* 40, 519-536.
- Nini, G., Smith, D., Sufi, A., 2012. Creditor control rights, corporate governance, and firm value. *Review of Financial Studies* 25, 1713-1761.
- Qi, J., Sutton, N.K., Zheng, Q., 2015. The value of strategic alliances in acquisitions and IPOs. *Financial Management* 44, 387-430.
- Roberts, M.R., Sufi, A., 2009. Control rights and capital structure: An empirical investigation. *Journal of Finance* 64, 1657-1695.
- Robinson, D., 2008. Strategic alliances and the boundaries of the firm. *Review of Financial Studies* 21, 649-681.
- Stuckey, J.A., 1983. Vertical integration and joint ventures in the aluminium industry. Harvard University Press, Cambridge, MA.
- Sufi, A., 2009. Bank lines of credit in corporate finance: An empirical analysis. *Review of Financial Studies* 22, 1057-1088.
- Zaheer, A., McEvily, B., Perrone, V., 1998. Does trust matter? Exploring the effects of interorganizational and interpersonal trust on performance. *Organization Science* 9, 141-159.

Table 1: Summary Statistics

This table summarises the sample. The panel data sample includes non-financial partners of strategic alliances from 1996 to 2011. All Compustat firms that violate or do not violate covenants are included. The firm characteristics are measured at the year immediately before the formation of alliances. All variables are defined in the appendix.

Variable	N	Mean	StdDev	Median
Log(1+Alliances/JV)	70,609	0.17	0.45	0.00
Log(1+JV)	70,609	0.07	0.33	0.00
Log(1+Alliances)	70,609	0.11	0.33	0.00
Ln(AT)	70,609	5.16	2.78	5.23
Violation	70,609	0.01	0.10	0.00
PPE/Assets	70,609	0.31	0.26	0.23
R&D/Assets	70,609	0.11	3.00	0.00
CAPEX/Assets	70,609	0.26	20.78	0.04
HI	70,609	0.22	0.39	0.06
HI ²	70,609	0.20	0.70	0.00
Ln(Age)	70,609	2.53	0.82	2.48
INST	70,609	0.24	1.42	0.02
Δ Tobin's Q	70,609	3.56	928.01	-0.02
Δ Leverage	70,609	0.11	25.38	0.00
Δ ROA	70,609	-2.41	509.29	0.00
Δ Net Worth/Assets	70,609	-0.76	117.74	0.00
Δ Current Ratio	70,609	-0.11	17.47	-0.01
Δ Interest/Assets	70,609	0.03	4.43	0.00
Δ Number of (Alliances/JV)	70,609	0.11	0.58	0.00

Table 2: Correlation of Variables Used in Analysis

This table presents the correlation of main variables used in our analysis. The panel data sample includes non-financial partners of strategic alliances from 1996 to 2011. All Compustat firms that violate or do not violate covenants are included. The firm characteristics are measured at the year immediately before the formation of alliances. All variables are defined in the appendix.

	Ln(1+ Alliance&JV)	Ln(1+JV)	Ln(1+ Alliances)	Ln(AT)	Violation	PPE/ Assets	R&D/ Assets	CAPEX /Assets	HI	Ln(Age)	INST	ΔTobin's Q	ΔLeverage	ΔROA	ΔNet Worth/ Assets	ΔCurrent Ratio	ΔInterest /Assets
Ln(1+ Alliance&JV)	1.0000***																
Ln(1+JV)	0.8370***	1.0000															
Ln(1+Alliances)	0.6151***	0.1038***	1.0000														
Ln(AT)	0.2291***	0.1783***	0.1610***	1.0000													
Violation	-0.0182***	-0.0157***	-0.0105***	-0.0313***	1.0000												
PPE/Assets	-0.0640***	-0.0906***	0.0149***	0.2124***	-0.0076**	1.0000											
R&D/Assets	-0.0034	-0.0019	-0.0033***	-0.0725***	-0.0023	-0.0223***	1.0000										
CAPEX/Assets	-0.0027	-0.0025	-0.0012***	-0.0113***	-0.0010***	0.0121***	-0.0003	1.0000									
HI	0.0564***	0.0779***	-0.0128***	-0.1364***	-0.0160***	-0.1281***	0.0091**	-0.0030	1.0000								
Ln(Age)	0.1113***	0.0731***	0.0995***	0.3475***	0.0074*	0.0209***	-0.0199***	-0.0040	-0.1442***	1.0000							
INST	0.0264***	0.0252***	0.0112***	0.0866***	-0.0056	-0.0195***	-0.0036	-0.0016	0.0016	0.0537***	1.0000						
ΔTobin's Q	-0.0012	-0.0012	-0.0005	-0.0244***	-0.0004	-0.0026	0.0371***	-0.0116***	-0.0025	-0.0049	-0.0007	1.0000					
ΔLeverage	-0.0012	-0.0011	-0.0006	-0.0303***	-0.0003	0.0030	0.1669***	-0.0128***	-0.0054	-0.0028	-0.0007	0.1168***	1.0000				
ΔROA	0.0014	0.0013	0.0006	0.0210***	0.0005	0.0037	-0.0191***	0.0013	0.0011	-0.0021	0.0008	-0.2424***	-0.0820	1.0000			
ΔNet Worth/Assets	0.0019	0.0017	0.0009	0.0295***	0.0006	0.0019	-0.0791***	0.0125***	-0.0003	0.0015	0.0011	-0.2080***	-0.4327	0.4845***	1.0000		
ΔCurrent Ratio	-0.0024	-0.0033	0.0005	0.0055	-0.0010	-0.0100***	-0.0011	0.0011	-0.0021	0.0049	0.0006	-0.0017	-0.0020	0.0001	0.0009	1.0000	
ΔInterest/Assets	-0.0018	-0.0017	-0.0008	-0.0348***	-0.0004	0.0002	0.1959***	-0.0045	-0.0052	-0.0044	-0.0010	0.0794***	0.8427	-0.0488***	-0.3740***	-0.0015	1.0000

Table 3: Raw Patterns on Alliance Formation Surrounding Covenant Violations

This table describes the raw pattern of alliance formation surrounding covenant violations. The sample includes the non-financial US firms that violate debt covenants at least once during 1996 to 2011. For each violating firm, we retain the number of alliances formed for a seven-year window centred at the violation year. We then run the following pooled regression:

$$\ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t} = \alpha + \beta_1 \text{Before}_{i,t}^{-1} + \beta_2 \text{Current}_{i,t} + \beta_3 \text{After}_{i,t}^1 + \beta_4 \text{After}_{i,t}^{2\&3} + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t}$$

The dependant variable in Column (1) is $\ln(1 + \text{Alliance\&JV})$, which is defined as the natural logarithm of 1 plus the number of alliances and JV formed by firm i in Year t . In Column (2) and (3), we use $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ as dependant variables, where the numbers of JV only or alliances only are counted respectively. $\text{Before}_{i,t}^{-1}$ is a dummy that equals 1 if the firm-year observation is in the year immediately before the firm's violation year and 0 otherwise. $\text{Current}_{i,t}$ is a dummy equals 1 if the firm-year observation is in the year when the violation occurs and 0 otherwise. $\text{After}_{i,t}^1$ is a dummy that equals 1 if the firm-year observation is in the year immediately after the firm's violation year and 0 otherwise. $\text{After}_{i,t}^{2\&3}$ is a dummy that equals 1 if the firm-year observation is in two or three years after the firm's violation year and 0 otherwise. Therefore, the benchmark is the observations two or three years before the violation year. Panel (A) reports the results with OLS regression. We also report the result using Tobit regression in Panel (B). t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. Standard errors are clustered by firm.

Panel A: OLS regression

VARIABLES	(1) alliance+JV	(2) JV only	(3) alliance only
Before ¹	0.003 (1.258)	0.001 (0.318)	0.002 (1.628)
Current	0.000 (0.303)	-0.000 (-0.018)	0.000 (0.543)
After ¹	-0.011*** (-3.551)	-0.009*** (-3.136)	-0.003** (-1.985)
After ^{2&3}	-0.017*** (-4.757)	-0.013*** (-3.995)	-0.005*** (-3.403)
Constant	-0.022 (-1.319)	-0.032*** (-2.793)	0.011 (1.226)
Observations	57,396	57,396	57,396
R-squared	0.028	0.026	0.016
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Panel B: Tobit Regression

VARIABLES	(1) Alliance&JV	(2) JV only	(3) alliance only
Before ¹	0.033*** (2.913)	0.016 (1.352)	0.085*** (3.712)
Current	0.002 (1.331)	0.001 (0.894)	0.004* (1.765)
After ¹	-0.101*** (-8.617)	-0.098*** (-8.057)	-0.170*** (-7.041)
After ^{2&3}	-0.172*** (-12.776)	-0.152*** (-10.981)	-0.327*** (-11.840)
Constant	-9.702*** (-590.070)	-9.831*** (-575.765)	-13.354*** (-414.746)
Observations	57,396	57,396	57,396
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 4: Regression of Number of Alliances on Covenant Violation

This table reports the OLS results of estimating the effect of firm's covenant violation on its number of alliances formed. Specifically, we run the following pooled OLS regression:

$$\ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t+n} = \alpha + \beta \text{Violation}_{i,t} + \gamma' \text{Controls}_{i,t} + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t}$$

The sample includes all the US non-financial firms during year 1996 to 2011 regardless of whether it violates covenants. The dependant variable in Panel A is $\ln(1 + \text{Alliance\&JV})$, which is defined as the natural logarithm of 1 plus the number of alliances and JV formed by firm i in Year $t+n$. Columns (1) to (3) reports the results of number measured in one($t+1$), two ($t+2$) or three ($t+3$) years accordingly. In Panel B and Panel C, we use $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ as dependant variables, where the numbers of JV only or alliances only are counted respectively. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. Standard errors are clustered by firm.

Panel A: Alliances & JV

VARIABLES	(1) Alliances&JV _{t+1}	(2) Alliances&JV _{t+2}	(3) Alliances&JV _{t+3}
Violation	-0.017** (-2.332)	-0.022** (-2.379)	-0.017** (-2.393)
Ln(AT)	0.035*** (4.329)	0.031*** (4.260)	0.028*** (4.283)
PPE/Assets	-0.112*** (-4.832)	-0.099*** (-4.656)	-0.089*** (-4.884)
R&D/Assets	0.132*** (5.178)	0.112*** (4.386)	0.099*** (4.305)
CAPEX/Assets	0.057* (1.934)	0.050* (2.050)	0.054** (2.750)
HI	0.127*** (3.462)	0.112*** (3.512)	0.097*** (3.741)
HI ²	-0.057*** (-4.260)	-0.051*** (-4.240)	-0.045*** (-4.301)
Ln(Age)	0.029*** (6.267)	0.026*** (5.565)	0.023*** (4.937)
INST	0.022 (1.546)	0.019 (1.538)	0.011 (1.095)
ΔTobin's Q	-0.000 (-1.081)	-0.000 (-0.133)	-0.000 (-0.751)
ΔLeverage	-0.004 (-1.535)	-0.000 (-0.023)	-0.002 (-1.003)
ΔROA	0.003** (2.612)	0.001 (1.144)	0.002** (2.706)
ΔNet Worth/Assets	-0.012*** (-4.565)	-0.009*** (-3.539)	-0.008*** (-4.754)
ΔCurrent	-0.001** (-2.795)	-0.001** (-2.357)	-0.000 (-0.321)
ΔInterest/Assets	0.021* (2.197)	0.014*** (3.479)	0.019* (2.159)
Constant	-0.241*** (-3.527)	-0.209*** (-3.460)	-0.207*** (-3.642)
Observations	70,609	70,609	70,609
R-squared	0.134	0.123	0.112
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Panel B: JV Only

VARIABLES	(1) JV _{t+1}	(2) JV _{t+2}	(3) JV _{t+3}
Violation	-0.010** (-2.435)	-0.017** (-3.098)	-0.013** (-2.644)
Ln(AT)	0.026*** (4.281)	0.024*** (4.345)	0.022*** (4.466)
PPE/Assets	-0.101*** (-4.023)	-0.088*** (-4.078)	-0.080*** (-4.177)
R&D/Assets	0.111*** (5.298)	0.097*** (4.420)	0.084*** (4.253)
CAPEX/Assets	0.050** (2.410)	0.046** (2.463)	0.054*** (3.620)
HI	0.116*** (3.589)	0.107*** (3.941)	0.095*** (4.037)
HI ²	-0.051*** (-4.237)	-0.047*** (-4.581)	-0.044*** (-4.524)
Ln(Age)	0.016** (2.828)	0.015** (2.719)	0.014** (2.722)
INST	0.025* (2.100)	0.022* (1.896)	0.016 (1.553)
ΔTobin's Q	-0.000* (-2.139)	-0.000 (-0.691)	-0.000 (-0.803)
ΔLeverage	-0.006** (-3.016)	0.002 (0.589)	-0.001 (-0.459)
ΔROA	0.002** (2.324)	0.000 (0.430)	0.001* (2.069)
ΔNet Worth/Assets	-0.010*** (-6.059)	-0.007*** (-3.626)	-0.007*** (-5.341)
ΔCurrent	-0.001*** (-3.534)	-0.001 (-1.361)	0.000 (0.067)
ΔInterest/Assets	0.012 (1.101)	0.009 (0.970)	0.014 (1.527)
Constant	-0.190*** (-3.745)	-0.167*** (-3.486)	-0.146*** (-3.481)
Observations	70,609	70,609	70,609
R-squared	0.107	0.102	0.098
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Panel C: Alliances Only

VARIABLES	(1) alliance _{t+1}	(2) alliance _{t+2}	(3) alliance _{t+3}
Violation	-0.008*** (-3.174)	-0.008** (-2.409)	-0.006** (-3.012)
Ln(AT)	0.013*** (4.411)	0.010*** (4.170)	0.009*** (4.195)
PPE/Assets	-0.025*** (-4.041)	-0.020*** (-3.658)	-0.016*** (-3.379)
R&D/Assets	0.044*** (3.596)	0.033*** (3.470)	0.028*** (3.612)
CAPEX/Assets	0.018 (1.243)	0.015 (1.287)	0.010 (1.172)
HI	0.011 (1.404)	0.009 (1.010)	0.009 (1.281)
HI ²	-0.006** (-2.293)	-0.004 (-1.434)	-0.005* (-1.853)
Ln(Age)	0.017*** (5.656)	0.013*** (5.927)	0.011*** (6.881)
INST	-0.009 (-0.879)	-0.006 (-0.686)	-0.007 (-0.916)
ΔTobin's Q	-0.000 (-0.448)	0.000 (0.263)	-0.000* (-1.920)
ΔLeverage	-0.001 (-0.966)	-0.002 (-1.303)	-0.002* (-2.067)
ΔROA	0.001** (2.546)	0.001 (1.610)	0.001* (2.003)
ΔNet Worth/Assets	-0.005*** (-3.744)	-0.004*** (-3.549)	-0.003*** (-3.554)
ΔCurrent	0.000 (0.103)	-0.000 (-1.262)	-0.000 (-1.437)
ΔInterest/Assets	0.015** (2.845)	0.011*** (3.260)	0.013*** (4.038)
Constant	-0.082** (-2.813)	-0.062** (-2.624)	-0.058*** (-3.280)
Observations	70,609	70,609	70,609
R-squared	0.057	0.044	0.038
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 5: Difference-in-Difference Results

This table presents the diagnostic test and DID results on whether covenants violation causes the reduction in number of alliances. For each nonfinancial US firm that is in new violation of debt covenants from 1996 to 2011, we match it with a nonfinancial firm that has not violated covenants in the previous years. We define firms in new violation as those that violate covenant in year t , but have not been in violation in the previous four quarters. The non-violating firms are restricted to those with outstanding loans. The matching is done by propensity score matching. We first estimate a probit regression of covenant violation on a group of firm characteristics. The dependant variable is a dummy that equals to 1 if a firm newly violates covenant in year t and 0 otherwise. The control variables are similar to those used in Section 3, and are measured at the year immediately before the violation. We also add the change in number of alliances to meet the parallel trend assumption.

$$Violation_{i,t} = \alpha + \gamma' Controls_{i,t-1} + Year_t + Industry_j + \varepsilon_{i,t}$$

The results are reported in the first column of Panel A. We then use the predicted probabilities to perform a nearest-neighbour propensity score matching, i.e., each violating firm is matched to a non-violating firm in the same industry and year with the closet propensity score. We also re-run the probit regression using the matched pairs and report the results in the second column of Panel A. Panel B compares the mean differences of the control variables between the treatment and control groups. Panel C reports the DID result. We compute the changes in alliance formation by taking the difference between the number of alliances over the three-year period after violation ($[+1, +3]$) and the number of alliances over the three-year period before violation ($[-3, -1]$), for treatment and control firms. The changes are also measured separately for alliance&JV, JV only and alliances only. Panel D uses the matched pairs and retain a seven-year window of observations centred at the violation year to run the following regression:

$$Ln(1 + Alliances\&JV / JV / Alliances)_{i,t} = \alpha + \beta_1 Violation * Current_{i,t} + \beta_2 Violation * After_{i,t} + \beta_3 Violation + \beta_4 Current_{i,t} + \beta_5 After_{i,t} + Year_t + Industry_j + \varepsilon_{i,t}$$

The dependant variables are $Ln(1 + Alliance\&JV)$, $Ln(1 + JV)$ and $Ln(1 + Alliances)$ in Column (1) to (3) respectively. *Violation* is a dummy that equals to one if the firm is in treatment group and 0 if it is in control group. *Current* _{i,t} is a dummy that equals one if the observation is in the violation year and 0 otherwise. *After* _{i,t} is a dummy that equals on if the firm is in the three-year period after violation year, and 0 otherwise. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. Standard errors are clustered by firm.

Panel A: Pre-match propensity score and post-match diagnostic regression

VARIABLES	(1) pre-match	(2) post-match
Ln(AT)	-0.068*** (-4.589)	0.002 -0.067
PPE/Assets	-0.231* (-1.813)	-0.061 (-0.253)
R&D/Assets	-0.836** (-2.324)	-0.155 (-0.454)
CAPEX/Assets	0.191 -1.348	0.063 -0.502
HI	-0.019 (-0.376)	-0.016 (-0.331)
Ln(Age)	0.008 -0.53	-0.013 (-0.529)
INST	0.378*** -7.358	-0.153*** (-2.954)
Δ Tobin's Q	0.003*** -4.785	0.001 -0.138
Δ Leverage	0.001 -0.043	0.027 -0.271
Δ ROA	-0.018*** (-3.008)	-0.023 (-1.083)
Δ Net Worth/Assets	0.042*** -4.167	0.110* -1.829
Δ Current Ratio	-0.012* (-1.748)	-0.006 (-0.559)
Δ Interest/Assets	-0.098* (-1.799)	0.326 -0.96
Δ Number of Alliances	-0.008 (-0.400)	0.03 -0.86
Constant	-2.201*** (-34.958)	0.086 -1.162
Observations	59,280	6,822
Pseudo R ²	0.065	0.003
Year FE	Yes	Yes
Industry FE	Yes	Yes

Panel B: Post-match differences

VARIABLES	Control	Treatment	Difference	P-value
Ln(AT)	4.757	4.704	0.053	0.303
PPE/Assets	0.288	0.285	0.003	0.519
R&D/Assets	0.043	0.042	0.001	0.728
CAPEX/Assets	0.083	0.085	-0.002	0.509
HI	0.221	0.224	-0.003	0.785
Ln(Age)	2.456	2.454	0.002	0.913
INST	0.265	0.243	0.022	0.013
Δ Tobin's Q	0.248	0.255	-0.007	0.952
Δ Leverage	0.047	0.028	0.019	0.052
Δ ROA	0.009	0.006	0.003	0.39
Δ Net Worth/Assets	0.079	0.033	0.046	0.018
Δ Current Ratio	-0.157	-0.165	0.008	0.83
Δ Interest/Assets	0.006	0.003	0.003	0.157
Δ Number of Alliances	-0.047	-0.016	-0.031	0.163

Panel C: DID estimate

VARIABLES	(1) Mean Control Difference (after-before)	(2) Mean Treatment Difference (after-before)	(3) Mean DID estimate (Treat-Control)	(4) P-values for DID estimate
Ln(1+Alliance&JV) (s.e.)	-0.093*** (0.009)	-0.135*** (0.010)	-0.042*** (0.013)	0.002
Ln(1+JV) (s.e.)	-0.054*** (0.008)	-0.081*** (0.008)	-0.027** (0.012)	0.025
Ln(1+Alliances) (s.e.)	-0.048*** (0.006)	-0.073*** (0.006)	-0.025*** (0.009)	0.004

Panel D: DID analysis for alliance numbers

VARIABLES	(1) Alliance&JV	(2) JV	(3) alliance
Violation*Current	-0.007 (-0.769)	-0.002 (-0.315)	-0.006 (-1.215)
Violation*After	-0.024*** (-3.731)	-0.014*** (-2.626)	-0.012*** (-3.174)
Violation	0.003 (0.740)	0.000 (0.013)	0.004 (1.554)
Current	0.000 (0.072)	0.002 (0.331)	-0.001 (-0.163)
After	0.003 (0.706)	0.002 (0.580)	0.002 (0.582)
Constant	0.032 (0.914)	0.019 (0.662)	0.013 (0.627)
Observations	48,321	48,321	48,321
R-squared	0.032	0.030	0.017
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 6: Regression Discontinuity Design (RDD) Results

This table presents the results of testing the effect of covenant violation on alliance formation using regression discontinuity design approach. The sample includes all firms which have covenants (restricting the current ratio or net worth of the firm) details covered in the Dealscan database from 1996 to 2011. We run the following regression:

$$\ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t} = \alpha + \beta_1 \text{Violation}_{i,t} + \beta_2 \text{Tobin's } Q_{i,t} + \beta_3 \text{ROA}_{i,t} + P_l(\text{CR}_{i,t}) + P_r(\text{CR}_{i,t}) + P_l(\text{NW}_{i,t}) + P_r(\text{NW}_{i,t}) + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t}$$

The dependant variables are $\ln(1 + \text{Alliance\&JV})$, $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ in Column (1) to (3) respectively. *Violation* is a dummy that equals 1 if a firm's current ratio or net worth falls below the corresponding covenant threshold in any quarters in a fiscal year. $P_l(\text{CR}_{i,t})$ and $P_r(\text{CR}_{i,t})$ are polynomial (2) in terms of current ratio measured from the left-hand and right-hand sides respectively. $P_l(\text{NW}_{i,t})$ and $P_r(\text{NW}_{i,t})$ are polynomial (2) in terms of net worth measured from the left-hand and right-hand sides respectively. Polynomial (2) is a polynomial of order two in terms of distance to default. Distance to default is the absolute difference between the firm's value and the corresponding threshold. If a firm does not violate covenants, we use the average distance of the four quarters to calculate Polynomial (2). If a firm violates covenants in only one quarter, we use the distance of the violating quarter. If a firm is in covenants violation for more than once, we use the maximum of the distance. Panel A reports the results using the entire sample. Panel B reports the results using the sample of narrow bands where the absolute value of the relative distance to the covenant threshold is less than or equals 0.2. Panel C reports the results using the sample of narrow bands where the absolute value of the relative distance to the covenant threshold is less than or equals 0.1. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. Standard errors are clustered by firm.

Panel A: Entire DealScan sample

VARIABLES	(1) Alliance&JV	(2) JV	(3) alliance
Violation	-0.009** (-2.801)	-0.006** (-2.685)	-0.022*** (-3.887)
Tobin's Q	0.007* (2.053)	0.006* (2.097)	0.005 (1.253)
ROA	0.011 (0.978)	0.005 (0.494)	0.038*** (3.436)
Constant	0.019 (1.499)	0.016 (1.627)	-0.015 (-0.310)
Observations	14,890	14,890	14,890
R-squared	0.038	0.025	0.076
Polynomial_2	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Panel B: Narrow bands around threshold Dealscan sample (distance to threshold <=0.2)

VARIABLES	(1) Alliance&JV	(2) JV	(3) alliance
Violation	-0.017** (-2.786)	-0.014*** (-3.451)	-0.003 (-1.132)
Tobin's Q	0.012 (1.668)	0.013* (1.853)	-0.001 (-1.178)
ROA	-0.005 (-0.172)	-0.014 (-0.519)	0.008 (0.918)
Constant	-0.057* (-2.098)	-0.059** (-2.459)	0.002 (0.442)
Observations	4,981	4,981	4,981
R-squared	0.071	0.064	0.035
Polynomial_2	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Panel C: Narrow bands around threshold DealScan sample (distance to threshold <=0.1)

VARIABLES	(1) Alliance&JV	(2) JV	(3) alliance
Violation	-0.019* (-2.150)	-0.014** (-2.376)	-0.007 (-1.463)
Tobin's Q	0.002 (0.657)	0.002 (0.791)	-0.001 (-0.334)
ROA	-0.060 (-1.672)	-0.054 (-1.472)	0.007 (0.342)
Constant	0.023 (0.708)	0.010 (0.296)	0.020*** (3.754)
Observations	2,226	2,226	2,226
R-squared	0.071	0.053	0.076
Polynomial_2	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 7: The Attenuating Need of Violating Firms to Form Alliances

This table tests whether the reduction in alliances is driven by the violating firm's side. In Panel A, we test whether the announcement return around alliance formation is significantly positive for the violating firms. The announcement return is measured by the cumulative abnormal return adjusted by Fama-French 3 factor model over the event windows of [-2, 1], [-3, 1], [-2, 2], [-5, 5] and [-7, 7]. We define the violating firms to be those violated covenants in the 1-year, 2-year and 3-year period before the alliance formation. In Panel B, we test whether there is a difference between the reductions in R&D alliances and non-R&D alliances following the firm's covenant violation. Specifically, we run the following regression:

$$\ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t} = \alpha + \beta_1 \text{Violation}_{i,t} + \beta_2 \text{R\&D Alliance}_{i,t} + \beta_3 \text{Violation}_{i,t} * \text{R\&D Alliance}_{i,t} + \gamma' \text{Firm_Controls}_{i,t-1} + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t}$$

The dependant variables are $\ln(1 + \text{Alliance\&JV})$, $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ in Column (1) to (3) respectively. *Violation* is a dummy that equals 1 if the firm violated covenants in the three years preceding alliance formation, and 0 otherwise. *R&D Alliance* is a dummy that equals 1 if the firm's average R&D expenditure measured over the past five years is above the industrial median and 0 otherwise.

Panel A: Announcement return around alliance formation for the violating firms

	(1)	(2)	(3)	(4)	(5)	Obs
Violation measured over past	[-2, 1]	[-3, 1]	[-2, 2]	[-5, 5]	[-7, 7]	
1-year	1.736%*** (3.067)	1.841%*** (3.051)	1.707%*** (2.800)	1.524** (2.262)	1.863%* (1.923)	355
2-year	1.454%*** (3.268)	1.476%*** (3.075)	1.562%*** (3.229)	1.214%* (1.791)	1.397* (1.781)	533
3-year	1.554%*** (3.883)	1.715*** (3.767)	1.625*** (3.767)	1.558** (2.552)	1.802*** (2.582)	648

Panel B: Reduction in R&D alliances V.S. non-R&D alliances

VARIABLES	(1) Alliance&JV	(2) JV	(3) Alliance
Violation	-0.025*** (-3.360)	-0.019** (-2.910)	-0.006* (-2.216)
R&D Alliance	0.054*** (3.946)	0.039** (3.126)	0.018** (2.384)
Violation*R&D Alliance	-0.003 (-0.161)	0.008 (0.573)	-0.014 (-1.351)
Ln(AT)	0.031*** (4.343)	0.021*** (3.884)	0.012*** (4.599)
PPE/Assets	-0.123** (-2.995)	-0.115*** (-3.205)	-0.013 (-1.231)
CAPEX/Assets	0.085* (1.950)	0.061* (1.995)	0.031* (1.879)
HI	0.149** (2.843)	0.136** (3.100)	0.016 (1.081)
HI ²	-0.059** (-2.257)	-0.052** (-2.357)	-0.008 (-1.192)
Ln(Age)	0.018*** (4.434)	0.006 (1.436)	0.014*** (5.176)
INST	0.016 (1.145)	0.027** (2.451)	-0.015 (-1.482)
ΔTobin's Q	0.000 (0.361)	-0.000 (-0.517)	0.000 (1.263)
ΔLeverage	0.004 (1.159)	0.002 (0.764)	0.002 (1.129)
ΔROA	0.001** (2.376)	0.000* (2.092)	0.001 (1.688)
ΔNet Worth/Assets	-0.007*** (-4.342)	-0.005*** (-3.526)	-0.003*** (-4.205)
ΔCurrent	-0.001*** (-3.957)	-0.001*** (-6.622)	0.000 (0.698)
ΔInterest/Assets	0.013 (1.567)	0.004 (0.645)	0.010** (2.319)
Constant	-0.125*** (-4.807)	-0.064** (-3.013)	-0.072*** (-4.562)
Observations	71,093	71,093	71,093
Adjusted R-squared	0.086	0.070	0.031
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 8: Reputation and the Relation between Covenant Violation and Alliance Formation

In this section, we test how the firm's reputation affects the relationship between covenant violation and alliance formation. Specifically, we run the following regression:

$$\ln(1 + \text{Alliances\&JV} / \text{JV} / \text{Alliances})_{i,t} = \alpha + \beta_1 \text{Violation}_{i,t} + \beta_2 \text{ReputationProxy} + \beta_3 \text{Violation}_{i,t} * \text{ReputationProxy} + \gamma' \text{Firm_Controls}_{i,t-1} + \text{Year}_t + \text{Industry}_j + \varepsilon_{i,t}$$

The dependant variables are $\ln(1 + \text{Alliance\&JV})$, $\ln(1 + \text{JV})$ and $\ln(1 + \text{Alliances})$ in Column (1) to (3) respectively. *Violation* is a dummy that equals 1 if the firm violated covenants in the three years preceding alliance formation, and 0 otherwise. For reputations proxies, we use two dummy variables: *Large* is a dummy that equals 1 if the firm's asset is greater than the median of the firms in the same year and industry, and 0 otherwise; *S\&P500* is a dummy that equals 1 if the firm is included in the S\&P500 index and 0 otherwise. We report the results using *Large* and *S\&P500* in Panel A and Panel B correspondingly.

Panel A: Firm size as proxy for reputation

VARIABLES	(1) Alliance&JV	(2) JV	(3) Alliance
Violation	-0.012** (-2.666)	-0.009** (-2.495)	-0.004** (-2.375)
Large	0.104*** (4.729)	0.074*** (4.002)	0.027*** (5.153)
Violation*Large	-0.059*** (-4.235)	-0.035** (-2.765)	-0.025*** (-6.779)
PPE/Assets	-0.093*** (-3.595)	-0.097*** (-3.803)	-0.001 (-0.182)
R&D/Assets	0.072** (2.941)	0.065** (2.936)	0.005 (1.338)
CAPEX/Assets	0.056 (1.672)	0.041 (1.794)	0.016 (1.587)
HI	0.132** (2.534)	0.124** (2.868)	0.008 (0.607)
HI ²	-0.053* (-1.933)	-0.048* (-2.102)	-0.005 (-0.741)
Ln(Age)	0.035*** (7.016)	0.018*** (3.665)	0.016*** (5.763)
INST	0.048*** (3.603)	0.047*** (3.865)	0.003 (0.539)
ΔTobin's Q	0.000 (0.706)	-0.000 (-0.176)	0.000* (1.982)
ΔLeverage	0.004 (1.725)	0.002 (1.017)	0.000 (0.281)
ΔROA	-0.000 (-0.241)	-0.000 (-0.554)	-0.000 (-1.498)
ΔNet Worth/Assets	0.004** (2.750)	0.003** (2.315)	0.001 (1.707)
ΔCurrent	-0.001*** (-5.121)	-0.001*** (-6.944)	-0.000 (-1.157)
ΔInterest/Assets	-0.018** (-3.136)	-0.017*** (-3.215)	-0.002* (-1.831)
Constant	-0.056*** (-3.473)	-0.017 (-1.117)	-0.036*** (-4.640)
Observations	70,556	70,556	70,556
Adjusted R-squared	0.055	0.049	0.015
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Panel A: S&P500 listing as proxy for reputation

VARIABLES	(1) Alliance&JV	(2) JV	(3) Alliance
Violation	-0.010*** (-3.302)	-0.008** (-2.719)	-0.004* (-2.206)
S&P500	0.310*** (5.687)	0.193*** (4.889)	0.111*** (4.827)
Violation*S&P500	-0.308** (-2.409)	-0.162 (-1.300)	-0.135*** (-5.361)
Ln(AT)	0.021*** (4.370)	0.015*** (3.831)	0.006*** (4.604)
PPE/Assets	-0.126*** (-3.534)	-0.119*** (-3.559)	-0.011 (-1.714)
R&D/Assets	0.109*** (3.718)	0.091*** (3.722)	0.016** (2.447)
CAPEX/Assets	0.065 (1.692)	0.048 (1.773)	0.018 (1.615)
HI	0.141** (2.959)	0.131** (3.155)	0.010 (0.878)
HI ²	-0.054* (-2.140)	-0.049** (-2.253)	-0.005 (-0.816)
Ln(Age)	-0.004 (-0.703)	-0.007 (-1.397)	0.003** (2.510)
INST	0.006 (0.444)	0.021* (1.941)	-0.013 (-1.545)
ΔTobin's Q	0.000 (0.991)	0.000 (0.271)	0.000* (2.019)
ΔLeverage	0.004 (1.404)	0.002 (0.834)	0.000 (0.103)
ΔROA	0.001** (3.020)	0.001 (1.704)	0.000 (0.640)
ΔNet Worth/Assets	-0.002 (-1.312)	-0.001 (-1.163)	-0.001 (-1.769)
ΔCurrent	-0.001*** (-4.261)	-0.001*** (-6.979)	-0.000 (-0.748)
ΔInterest/Assets	-0.004 (-0.631)	-0.007 (-1.199)	0.001 (1.112)
Constant	-0.021* (-2.044)	0.002 (0.189)	-0.021*** (-4.478)
Observations	70,609	70,609	70,609
Adjusted R-squared	0.132	0.096	0.048
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 9: Covenant Violation and Announcement Return of Alliance Formation

This table presents the result of testing whether forming an alliance with a recently covenant violating partner affect the announcement return adversely. Specifically, we run the following regression:

$$CAR_{i,t} = \alpha + \beta_1 Partner_Violation_{i,t} + \beta_2 Self_Violation_{i,t} + \gamma' Firm_Controls_{i,t-1} + \delta' Deal_Controls_{i,t} + Year_t + Industry_j + \varepsilon_{i,t}$$

The dependant variable is $CAR_{i,t}$, which is defined as the firm's cumulative abnormal return adjusted by Fama-French 3 factors measured around the alliance formation. The event window is [-2, 1], [-3, 1], [-2, 2], [-5, 5] and [-7, 7] respectively from Column (1) to Column (5). $Partner_Violation_{it}$ is a dummy that equals to one if the firm's partner has been in covenant violation for at least once in the three years preceding the alliance formation and 0 otherwise. $Self_Violation_{it}$ is a dummy that equals one if the firm itself has been in covenant violation for at least once in the three years preceding the alliance formation and 0 otherwise. The firm characteristics measured in the year immediately preceding the alliance formation are controlled. We also control for deal characteristics: JV is a dummy that equals one if the partnership is formed as JV and zero otherwise; Relsize is a dummy that equals one if the relative size of the firm to its partner is less than the median of firms in the same year and industry, and zero otherwise; Horizontal is a dummy that equals to one if the firm and its partner are from the same industry and zero otherwise. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. Standard errors are clustered by industry.

VARIABLES	(1) [-2, 1]	(2) [-3, 1]	(3) [-2, 2]	(4) [-5, 5]	(5) [-7, 7]
Partner-Violation	-0.007*** (-3.319)	-0.007** (-3.109)	-0.008*** (-3.313)	-0.007** (-2.440)	-0.009*** (-3.403)
Self-Violation	-0.005 (-1.048)	-0.004 (-0.610)	-0.003 (-0.857)	-0.001 (-0.120)	0.005 (0.473)
Ln(AT)	-0.005*** (-10.369)	-0.004*** (-7.605)	-0.004*** (-8.355)	-0.003** (-2.495)	-0.002* (-2.206)
PPE/Assets	-0.007 (-0.961)	-0.005 (-0.601)	-0.009 (-1.607)	0.003 (0.269)	-0.004 (-0.371)
R&D/Assets	0.051** (2.707)	0.042*** (5.867)	0.067** (2.780)	0.042*** (3.673)	0.074*** (6.161)
CAPEX/Assets	-0.005 (-0.252)	-0.014 (-0.567)	-0.010 (-0.432)	-0.048 (-1.189)	-0.033 (-0.723)
HI	-0.001 (-0.561)	-0.001 (-0.369)	-0.002 (-0.736)	0.001 (0.274)	-0.003 (-0.603)
Ln(Age)	-0.002** (-2.491)	-0.002 (-1.630)	-0.001 (-1.261)	-0.001 (-0.427)	-0.001 (-0.448)
INST	-0.007** (-2.392)	-0.009** (-2.452)	-0.004 (-1.502)	-0.004 (-0.616)	-0.003 (-0.434)
ΔTobin's Q	-0.001*** (-5.846)	-0.001*** (-5.649)	-0.001*** (-4.295)	-0.002*** (-5.799)	-0.002*** (-4.583)
ΔLeverage	0.015** (2.247)	0.017*** (3.191)	0.024*** (4.523)	0.046*** (5.118)	0.040*** (4.512)
ΔROA	-0.002 (-0.352)	-0.001 (-0.147)	0.005 (0.687)	0.024** (2.336)	0.020*** (4.729)
ΔNet Worth/Assets	-0.005* (-1.981)	-0.018* (-1.958)	0.001 (0.470)	-0.025** (-2.428)	-0.014 (-0.988)
ΔCurrent Ratio	-0.000 (-0.228)	-0.000 (-0.304)	0.000 (0.055)	0.001 (1.332)	0.001 (1.419)
Std	-0.010 (-0.045)	-0.241 (-1.011)	0.014 (0.048)	-0.322 (-0.631)	-0.442 (-0.517)
JV	0.003 (0.738)	0.003 (0.545)	0.002 (0.415)	0.004 (0.460)	0.004 (0.543)
Par-Violation*JV	0.001 (0.155)	-0.007 (-0.554)	0.001 (0.084)	-0.013 (-0.998)	-0.005 (-0.444)
Resize	-0.004 (-1.621)	-0.004 (-1.700)	-0.003 (-1.406)	-0.004* (-1.845)	-0.006** (-2.924)
Horizontal	0.002** (2.259)	0.001 (0.819)	0.002 (1.231)	0.001 (0.622)	0.003 (0.998)
Constant	0.046** (2.300)	0.060** (2.932)	0.029 (1.309)	0.008 (0.169)	0.015 (0.214)
Observations	6,521	6,520	6,521	6,520	6,520
R-squared	0.050	0.050	0.040	0.034	0.026
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Table 10: Firm's cumulative abnormal return around its partner's covenant violation date

This table reports the firm's cumulative abnormal return (CAR) around the date when its partner violates covenant. We compute CAR adjusted by Fama-French 3 factors for the event windows of [-2, 1] and [-3, 1], and present the mean in Column 3 and Column 4 respectively. We do not distinguish between alliance and JV. Panel A reports the results using all alliance & JV. Panel B reports the mean of CAR for small and large firms, and tests the mean difference of the two groups. Small firms are those with relative size smaller than the median of firms in the same year and industry. Large firms are those with relative size larger than the median of firms in the same year and industry. Panel C reports the mean of CAR for firms with high and low R&D, and tests the mean difference of the two groups. Firms with high R&D are those with R&D/Assets ratios higher than the median of firms in the same year and industry. Firms with low R&D are those with R&D/Assets ratios lower than the median of firms in the same year and industry. Panel D reports the mean of CAR for constrained and liquid firms, and tests the mean difference of the two groups. Constrained firms are those with WW financial constraint indices higher than the median of firms in the same year and industry. Liquid firms are those with WW financial constraint indices lower than the median of firms in the same year and industry. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

	Observation	CAR[-2, 1]	CAR[-3, 1]
<i>Panel A: All Alliance & JV</i>			
	6355	-0.057% (-0.785)	-0.024% (-0.300)
<i>Panel B: Small vs Large</i>			
Small	3085	-0.268% ** (-2.212)	-0.238% * (-1.765)
Large	3085	0.125% (1.440)	0.154% 1.613
Small-Large		-0.393% *** (2.636)	-0.392% ** (2.373)
<i>Panel C: High R&D vs Low R&D</i>			
High	2642	-0.250% ** (-2.086)	-0.284% ** (-2.155)
Low	2642	0.060% (0.505)	0.134% 1.011
High-Low		-0.310% * (1.814)	-0.418% ** (2.216)
<i>Panel D: Constrained vs Liquid</i>			
Constrained	3011	-0.275% ** (-2.111)	-0.260% * (-1.797)
Liquid	3011	0.130% * (1.682)	0.201% ** (2.326)
Constrained-Liquid		-0.405% *** (2.671)	-0.461% *** (2.735)

Appendix: Variable definitions

Variables	Definition
Alliance Measures	
Ln(1+alliance&JV)	Natural logarithm of one plus the total number of alliance and JV measured in a given time period
Ln(1+ JV)	Natural logarithm of one plus the total number of JV measured in a given time period
Ln(1+ alliance)	Natural logarithm of one plus the total number of alliance only measured in a given time period
Firm Characteristics	
Ln (AT)	Natural logarithm of total assets
PPE/Assets	Net property, plant and equipment divided by total assets
R&D/Assets	Research and development expenditures divided by total assets
CAPEX/Assets	Capital expenditure divided by total assets
HI	Herfindahl index based on annual sales in each 4-digit industry
(Δ)Tobin's Q	(Change in)Ratio of market value of assets to book value of total assets
Ln(Age)	Natural logarithm of number of years since the firms appeared in Compustat
INST	Institutional ownership calculated as the arithmetic mean of the four quarterly institutional holdings reported in form13F
(Δ)Leverage	(Change in) Ratio of book value of total debt to total assets
(Δ)ROA	(Change in) Ratio of operating cash flow to total assets
(Δ)Net Worth/Assets	(Change in) Ratio of net worth (total assets minus total liabilities) to total assets
(Δ)Current Ratio	(Change in) Ratio of total current assets to total current liabilities
(Δ)Interest/Assets	(Change in) Ratio of interest expense to total assets
Δ Number of alliances	Change in number of alliance and JV
STD	The return volatility measured over the previous four quarters

Essay Three: Does Corporate Hedging Affect Firm Value? Evidence from the IPO Market

Abstract

Focusing on the IPO market, this study examines the influence of corporate hedging on firm value. Since corporate hedging reduces the information asymmetry of IPO firms, we find that the issuers with corporate hedging have less information to extract from informed investors and are associated with lower price revisions and underwriting fees. More importantly, corporate hedging is found to reduce IPO underpricing, which provides evidence that hedging increases firm value particularly during the issuing process. We also provide further evidence that corporate hedging increases firm value through the channel of reducing information asymmetry and value uncertainty, by documenting that hedging reduces the aftermarket idiosyncratic volatility and enhances aftermarket liquidity and long-term performance.

JEL Classification: G14; G32; G34

Keywords: Corporate Hedging; Firm Value; IPO

1. Introduction

An important topic under debate in corporate finance is whether corporate hedging affects firm value. In the frictionless regime of Modigliani and Miller (1958), hedging should not matter. However, this theory is not consistent with the phenomenon of widely used risk management by corporations. Among the various explanations about the relationship between corporate hedging and firm value (Stulz, 1984; Smith and Stulz, 1985; Froot et al., 1993; Bessembinder, 1991; Campbell and Kracaw, 1990), DeMarzo and Duffie (1995) argue that corporate hedging allows investors to learn better about the management ability and project quality from the firm's performance, hence make better investment decisions. The reduction in information asymmetry leads to the positive effect of corporate hedging on firm value. On the empirical studies side, Allayannis and Weston (2001), Carter et al. (2006) and Perez-Gonzalez and Yun (2013) document positive relationship between corporate hedging and firm value, while Tufano (1996) and Jin and Jorion (2006) find no relationship. We add to the debate by studying the performance of hedged issuers versus not-hedged issuers in the IPO market.

Specifically, we follow DeMarzo and Duffie's (1995) argument and hypothesize that corporate hedging reduces the information asymmetry and value uncertainty faced by the IPO firm and increases its valuation particularly in the issuing process. We focus on the IPO market because the IPO firms are typically younger, smaller and more obscure, and hence suffer from higher levels of information asymmetry. The effect of corporate hedging should be stronger for the issuers. Second, the IPO setting provides another measure of firm value besides the typically used *Tobin's Q*: IPO underpricing. If the IPO investors value the issuer more and ask for a lower compensation, it will translate into a lower level of underpricing and cost of raising external capital. Third, we argue that the incentive of corporate hedging is higher for IPO firms, if there is a positive relationship between hedging and firm value. This

is because a higher valuation of the issuing firm in the IPO process effectively reduces the money left on the table and benefits the initial management teams.

Our intuition is also consistent with the asymmetric information models of IPO underpricing. First, Beatty and Ritter (1986) demonstrate that the level of underpricing is positively related to the ex-ante uncertainty about the value of IPO firms, as the higher uncertainty induces a higher proportion of informed investors and aggravates the winner's curse problem of Rock (1986). Since corporate hedging reduces the uncertainty of IPO firm's value, it should help to lower underpricing. Second, the bookbuilding theory (Benveniste and Spindt, 1989; Benveniste and Wilhelm, 1990; Spatt and Srivastava, 1991; Sherman and Titman, 2002) argues that IPO underpricing is a mechanism to elicit the truth telling from informed investors. Consistent with the theory, corporate hedging should reduce the IPO underpricing and price revision, since it reduces the need of information extraction from investors by lowering information asymmetry.

For the 2087 IPO firms from 1996 to 2009, we find empirical evidences to support the story that corporate hedging reduces information asymmetry and hence increases firm value of issuers. Our measure of corporate hedging is a set of dummy variables about whether the firm uses financial derivatives to hedge against interest rate risk or foreign exchange rate risk (*Hedging*), interest rate risk (*Interest Hedging*) or exchange rate risk (*FX Hedging*). First, we document that corporate hedging reduces IPO price revision. The price revision of issuers with corporate hedging is lower than those without hedging, suggesting that less information is extracted from bookbuilding for the hedged firms. The difference is economically significant, which ranges from 0.031 to 0.068 depending on the model specification. Along this line, the underwriting fee is found to be lower for IPO firms with corporate hedging, which is consistent with the weakened role of underwriters in bookbuilding. We then study the effect of corporate hedging on IPO underpricing directly. First, the corporate hedging is

documented to be negatively related IPO underpricing at 1% significance level. The differences in IPO underpricing between firms with and without corporate hedging range from 0.067 to 0.087, or 26.40% to 35.20% of the average underpricing in our sample, which translate in to an average value increase of \$14.04m to \$18.72m. Consistent with the intuition that corporate hedging reduces the value uncertainty of issuers, we next find that IPO aftermarket volatility is smaller for firm with corporate hedging. Lastly, consistent with the effect of corporate hedging on reducing the information asymmetry between informed and uninformed investors, we show that post-IPO liquidity and long-term performance are positively associated with corporate hedging.

The rest of the paper is organized as follows. Section 2 discusses related literature. Section 3 describes the data selection and variable construction. Section 4 presents the empirical results. Section 6 concludes the paper.

2. Literature Review

The first strand of related literature is on the relationship between corporate hedging and firm value. There are several theories explaining why corporate hedging should affect firm value. Smith and Stulz (1985) argue that hedging can reduce the probability of bankruptcy and hence increase firm value. In the same paper, they also suggest that the convexity structure of tax may be a reason why corporate hedging affects firm value, in the sense that hedging can reduce the expected tax payment. Froot et al. (1993) propose that for firms with financial constraint, hedging can reduce the underinvestment problem that arises from the variation in cash flow and costly external financing. More related to our study is the asymmetric information model of DeMarzo and Duffie (1995). They argue that by corporate

hedging, investors can learn better about the management ability and project quality from the firm's performance, hence make better investment decisions. As a result, corporate hedging leads to a higher firm value. Empirically, Manconi et al. (2016) find that hedging reduces the value uncertainty and information asymmetry of firms.³

On the empirical study side, the evidences are mixed. Allayannis and Weston (2001) find that the use of foreign currency derivative causes a 4.87% increase of firm value for large non-financial firms. Carter et al. (2006) document a similar result by examining the U.S. airline industry. Perez-Gonzalez and Yun (2013) use a natural experiment of weather derivative introduction and find a positive relationship between hedging and firm value. Some other studies document the underlying channels through which corporate hedging affects firm value. For example, Graham and Rogers (2002) show that hedging increases the firm's debt capacity. Campello et al. (2011) document that hedging firms are associated with lower interest spreads and smaller likelihoods of capital expenditure restrictions. However, Tufano (1996) doesn't find a significant relationship between hedging and firm value for the gold mining industry. Jin and Jorin (2006) also find no significant relationship from the U.S. oil and gas producers. In addition, Guay and Kothari (2003) question the importance of hedging by showing that derivative use appears to be a small proportion of overall risk profile for the non-financial firms. We add to the debate by showing that the use of financial derivatives increases the value of IPO firms.

Another strand of related research is on IPO. Most related to our study are two asymmetric informational models of IPO underpricing. First, the winner's curse model by Rock (1986) argues that the information heterogeneity of investors leads to the IPO underpricing as the uninformed investors need the compensation. Based on Rock's (1986) model, Beatty and Ritter (1986) show that the level of IPO underpricing should be positively

³ DaDalt et al. (2002) also provide direct evidence that the use of derivatives lowers information asymmetry.

related to the ex-ante uncertainty of the issuer's value. They argue that an investor who engages in information acquisition implicitly invests in a call option on the IPO, with the offer price as strike. Since the value of the option increases with the valuation uncertainty, more investors will decide to acquire information if the IPO value is more uncertain. Therefore, the winner's curse problem is exaggerated and the underpricing is higher. Second, the bookbuilding/information revelation theory (Benveniste and Spindt, 1989; Benveniste and Wilhelm, 1990; Spatt and Srivastava, 1991; Sherman and Titman, 2002) assumes that there is information asymmetry between informed investors and underwriters, and suggests that underpricing is used to elicit truth telling and extract information from the informed investors.

There are several empirical studies that demonstrate IPO underpricing can be reduced by lowering the information asymmetry of issuers. Booth and Smith (1986), Carter and Manaster (1990), Michaely and Shaw (1994) and Titman and Trueman (1986) show that by hiring prestigious intermediaries to certify the quality and reduce information asymmetry of issuers, the IPO firms are associated with lower levels of underpricing. Hanley and Hoberg (2010) find that IPO firms with more information contained in the form S-1 are associated with lower price revision and underpricing. Loughran and McDonald (2013) study the tone of form S-1, and find that IPOs with higher level of uncertain text are associated with higher underpricing, absolute price revision and aftermarket volatility. Chemmanur and Paeglis (2005) document that higher management quality has a certifying effect on firm value and reduces information asymmetry of IPO firms, hence lowers underpricing and underwriting fee and enhances post-IPO long-term performance. We add to the literature by showing that corporate hedging reduces information asymmetry and value uncertainty of IPO firms and hence lowers IPO underpricing.

3. Hypotheses Development

By corporate hedging, firms allow their investors to learn better about the management ability and project quality from corporate earnings, hence reduce the information asymmetry between firms and investors (DeMarzo and Duffie, 1995). When the corporate earning is more informative and the ex-ante uncertainty of IPO firm value is smaller, the incentive for investors to produce their own information is reduced, which in turn ameliorates the information heterogeneity among investors. Also, the underwriter has a lower cost of information acquisition and can better interpret the accounting information of IPO firms, hence suffers less from information asymmetry with informed investors. Therefore, corporate hedging reduces information asymmetry not only between informed and uninformed investors, but also between underwriter and informed investors. This intuition is the basis of our hypotheses.

Our first set of hypotheses is related to corporate hedging and underwriting. Since corporate hedging reduces the information asymmetry in the IPO process, there is less information the underwriter need to extract from investors during the book-building. Therefore, we would expect that price revision, which is a measure of information released during bookbuilding (Hanley, 1993), is smaller for IPOs that have corporate hedging. In addition, underwriter should be less important for IPOs with hedging, hence charge a lower fee.

H1: There is a negative relationship between the level of an IPO's price revision and its corporate hedging.

H2: The underwriting fee for an IPO with corporate hedging is lower compared to an IPO without hedging.

The second set of hypotheses deals with the relationship between corporate hedging and IPO underpricing, post-IPO volatility, post-IPO illiquidity and post-IPO long-term performance.

If corporate hedging lowers information asymmetry, there is less need to leave money on the table to induce the truth-telling from informed investors. Also, the winner's curse problem from the information asymmetry between informed and uninformed investors is reduced. As a result, corporate hedging lowers the level of IPO underpricing.

H3: The level of IPO underpricing is negatively related to corporate hedging.

To support our story that corporate hedging reduces IPO underpricing via the channel of lowering information asymmetry, we also develop some hypotheses regarding IPO characteristics.

First, if corporate hedging reduces information asymmetry and value uncertainty of the issuing firm, the IPO with corporate hedging should be viewed as less risky. Following Ritter (1984), we measure risk of IPO stocks by aftermarket volatility, and propose the following hypothesis:

H4: The post-IPO stock volatility is negatively related to corporate hedging.

Next, the reduction in information asymmetry among investors by corporate hedging attracts more dispersed investors and creates higher post-IPO liquidity.⁴

H5: The post-IPO stock illiquidity is negatively related to corporate hedging.

Lastly, as argued by Morris (1996), Chen et al. (2002) and Duffie et al. (2002), the long-term underperformance of IPOs is caused by heterogeneous expectations among

⁴ Booth and Chua (1996) argue that issuers leave money on the table to enlarge the pool of shareholder and create higher liquidity in the aftermarket, which in turn raises firm value.

investors about the firm's future cash flow and the cost associated with short-selling the shares of IPO stocks. If corporate hedging leads to a reduction in information asymmetry and heterogeneity among investors, the aftermarket IPO long-term performance should be higher.

H6: The post-IPO long-term performance is positively associated with corporate hedging.

4. Data and Main Variables

4.1 Data and Sample Selection

Our data on major IPO characteristics comes from Thomson Financial's SDC New Issue database. We start with all the US firms that went public between 1996 and 2009. We then exclude 1) unit offers, REITs, ADRs and deals with offer price below five dollars; 2) financial IPO firms with SIC codes from 6000 to 6999; 3) IPO firms that miss important control variables for our analysis; 4) IPO firms that are not covered by Center for Research in Security Prices (CRSP) database.

Some other important IPO variables: founding date of IPO firms, ranking of lead underwriters and coverage of star analysts are obtained from Jay Ritter's website. The data of stock price, stock return and trading volume are from CRSP. The information of outstanding bond is from Mergent FISD and Lipper/eMAXX fixed income database. Our final sample consists of 2087 IPOs of non-financial US firms from 1996 to 2009.

4.2 Measures of Corporate Hedging

We rely on Capital IQ corporate filings database for hedging information. Following previous literature (Allayannis and Weston, 2001; Campello et al., 2011; Purnanandam, 2008), we focus on the use of financial derivatives to hedge against interest rate risk or

exchange rate risk. Specifically, we search for keywords (described in details in the paragraphs below) related to firm's use of financial derivative against interest rate risk or exchange rate risk from the company filing reports in Capital IQ. Since Capital IQ does not allow mass-downloading of the reports, we measure hedging activities using hedging dummies. A company is defined to be a hedger (*Hedging*=1) in *Year t* if its filings in the previous three years contain the keywords, and *Hedging*=0 otherwise.⁵

For interest rate risk hedging, we use the following keywords: “interest rate swap”, “interest rate cap”, “interest rate collar”, “interest rate floor”, “interest rate forward”, “interest rate forward”, “interest rate option” and “interest rate future”.

For exchange rate risk hedging, we use the following keywords: “foreign exchange forward”, “forward foreign exchange”, “foreign exchange rate forward”, “currency forward”, “currency rate forward”, “foreign exchange option”, “currency option”, “foreign exchange rate option”, “currency rate option”, “foreign exchange future”, “currency rate future”, “foreign exchange swap”, “currency swap”, “foreign exchange rate swap”, “currency rate swap”, “foreign exchange cap”, “currency cap”, “foreign exchange rate cap”, “currency rate cap”, “foreign exchange collar”, “currency collar”, “foreign exchange rate collar”, “currency rate collar”, “foreign exchange floor”, “currency floor”, “foreign exchange rate floor” and “currency rate floor”.

We also distinguish the interest rate hedging and exchange rate hedging by creating two separate dummies: *Interest Hedging* =1 if the IPO firm's filings in the previous three years contain the keywords about interest rate risk hedging as described in the above, and 0 otherwise; *FX Hedging* =1 if the IPO firm's filings in the previous three years contain the keywords about exchange rate risk hedging as described in the above, and 0 otherwise.

⁵ We hand checked the filings to ensure that the financial derivatives as mentioned by the keywords are actually used by the hedgers.

4.3 Other variables

We now define the main control variables. *Firm Age before IPO* is the log number of years between the foundation date and IPO date; *IPO Size* is the log value of total proceeds raised from IPO; *Bond Outstanding Dummy* is a dummy that equals to 1 if the firm has outstanding public bonds before IPO and 0 otherwise; *Nasdaq Dummy* is a dummy that equals to 1 if the IPO stock is listed on Nasdaq and 0 otherwise; *High Tech Industry Dummy* is a dummy that equals to 1 if the IPO firm is in the high-tech industry and 0 otherwise; *Financial Center* is a dummy that equals to 1 if the IPO firm's headquarter is located in New York or California State, and 0 otherwise; *Insider Ownership* is the percentage of shares held by the insiders before IPO; *Lock Period* is the number of years for which the shares held by insiders are in lockup; *Venture-capital Backed Dummy* is a dummy that equals to 1 if the IPO is backed by venture capital and 0 otherwise; *High Ranked Underwriter Dummy* is a dummy that equals to 1 if the IPO's underwriter is ranked above 7 and 0 otherwise; *Number of Underwriters* is the number of underwriters involved in the IPO; *Star-analyst Coverage Dummy* is a dummy that equals to 1 if the IPO firm is covered by star-analysts within one year after IPO and 0 otherwise; *Recent Market Returns* is the value-weighted market return in the previous month of IPO; *Recent Market-average IPO Premium* is the average IPO underpricing in the previous month of IPO; *Recent Market IPO Volume* is the log value of total IPO proceeds raised in the previous month of IPO. *Quality* is the post IPO event firm performance, measured as the 4-digit industry adjusted return measured over the one-year period from $t+1$ to $t+2$, where t is the offer date.

We have several independent variables. *IPO Price Revision* is defined as $(\text{Offer Price} - \text{Middle Filing Price}) / \text{Middle Filing Price}$. *IPO Underwriting Fee* is the percentage of underwriting fee and selling concessions to proceeds. *IPO Underpricing* is the adjusted return

on the first day of trading, defined as (1st day closing price-offer price)/offer price-1st day market return. *After-market Idiosyncratic Volatility* is defined as the standard deviation of the residual from regression using Fama-French 3 factor model over the one quarter period after IPO. *After-market Amihud Illiquidity* is defined as the average of Amihud illiquidity measure over the one quarter period after IPO, where Amihud illiquidity is calculated as $1000 * \sqrt{|R_{i,t}| / DVol_{i,t}}$ ($R_{i,t}$ is the daily stock return, and $DVol_{i,t}$ is the daily dollar volume of stock i at day t). *After-market IPO Performance* is defined as the 4-digit industry adjusted return measured over the one-year period after IPO. We also include year and/or industry fixed effects, given that IPO underpricing is sensitive to economic conditions and there is clustering in IPO underpricing within industries.

The summary statistics are reported in Table 1. Panel A of Table 1 summarizes the main variables. Among the sample firms from 1996 to 2009, we find that 24% of them hedge against interest rate risk, and 10% hedge against exchange rate risk. Overall, 28% of the IPO firms hedge against interest rate risk or exchange rate risk. Other IPO characteristics are similar to previous literature: 3% of the IPO firms have bonds outstanding, 77% of the IPO firms are listed on NASDAQ, 63% of the IPO firms are from high-tech industry and 48% of the IPO firms are backed by venture capitals. On average, firms take 9.39 years to go IPO and experience underpricing of 25%. We also split the sample into industries based on Fama-French 12 industry classification, and summarize the hedging information in Panel B of Table 1. The proportions of hedged issuers range from 14% to 63% across different industries. Within each industry, there is also significant variation of hedging usage.

[Table 1 about here]

5. Empirical Results

5.1 Underwriter and IPO firm hedging

5.1.1 Corporate hedging and IPO price revision

To test the relationship between IPO price revision and corporate hedging (hypothesis H1), we run the following regression:

$$IPO\ Price\ Revision_i = \alpha + \beta * Hedging_Measure_i + \delta' X_i + \varepsilon_i$$

For *Hedging_Measures*, we use three sets of dummy variables: *Hedging_i*, *Interest Hedging_i* and *FX Hedging_i* as mentioned in Section 4. *X_i* is a set of control variables also described in Section 4. If corporate hedging reduces IPO price revision, the coefficients of *Hedging_Measures* should be significantly negative.

The results are reported in Table 2. In Columns (1)-(2), the variable of interest is the dummy variable *Hedging*, where we do not distinguish between types of financial derivatives. We first include only year fixed effect and then include both year and industry fixed effects. The results show that corporate hedging reduces IPO price revision at 1% significance level. For example, when both year and industry fixed effects are included, the IPOs with corporate hedging have price revisions 0.039 lower than the IPOs without hedging. The economic difference is also significant, given that the mean of IPO price revision is -0.01 in our sample. We then separate *Hedging* to interest rate risk hedging and foreign exchange rate risk hedging, and reports the results in column (3)-(4) and column (5)-(6) respectively. The coefficients of hedging measures are all highly significantly negative. For example, when both year and

industry fixed effects are included, *Interest Hedging* reduces price revision by 0.034 and *FX Hedging* reduces price revision by 0.068 at 1% significance level.⁶

[Table 2 about here]

Control variables also have consistent coefficients with theoretical intuitions. For example, IPO firms with longer history should have lower information asymmetry, and the results show that they are associated with lower price revision, which is consistent with previous literature (Lowry and Schwert, 2004).

5.1.2 Corporate hedging and underwriting fee

If eliciting information from informed investors is less crucial for IPO firms with corporate hedging, the contribution of underwriters in bookbuilding is less valued. In equilibrium, this will translate into a lower underwriting fee charged by investment banks. The lower underwriting fee is also a direct benefit to issuers. We hence test the relationship between corporate hedging and underwriting fee (hypothesis H2), to provide further evidence that corporate hedging reduces information asymmetry of issuers. Specifically, we run the following regression:

$$Underwriting\ Fee_i = \alpha + \beta * Hedging_Measure_i + \delta'X_i + \varepsilon_i$$

The *Hedging_Measures* include *Hedging_i*, *Interest Hedging_i* and *FX Hedging_i*. X_i is a set of control variables described in Section 4. We expect the coefficients of *Hedging_Measures* to be significantly negative.

The results are reported in Table 3. In Columns (1)-(2), the variable of interest is the dummy variable *Hedging*. We first include only year fixed effect and then include both year

⁶ Loughran and McDonald (2013) argue that the effect of IPO uncertainty on price revision is better captured by absolute price revision. In untabulated tests, we use the absolute value of IPO price revision as dependent variables, the results are similar.

and industry fixed effects. The coefficients of *Hedging* are significantly negative at 1% level, suggesting that corporate hedging effectively reduces underwriting fee. For example, when only year fixed effect is included, the result shows that IPO firms with corporate hedging pay underwriting fees 0.103 (1.46% of the average fee within our sample) lower than those without hedging. We then separate *Hedging* to interest rate risk hedging and foreign exchange rate risk hedging, and reports the results in column (3)-(4) and column (5)-(6) respectively. The coefficients of hedging measures are all highly significantly negative. For example, when both year and industry fixed effects are included, *Interest Hedging* reduces underwriting fee by 0.096 and *FX Hedging* reduces underwriting fee by 0.101 at 1% significance level.

[Table 3 about here]

Overall, we find evidence that underwriter extracts less information from informed investors and consequently charges lower fee, if the issuer has corporate hedging. The evidences suggest that corporate hedging reduces the information asymmetry between underwriters and informed investors.

5.2 Corporate Hedging and IPO Results

In this section, we study the effect of corporate hedging on IPO results, specifically the IPO underpricing, post-IPO idiosyncratic volatility, post-IPO stock liquidity and long-term performance.

5.2.1 Corporate hedging and IPO underpricing

IPO underpricing is a direct cost to a firm, since the issuer can otherwise raise higher capital from the market. Hence, the valuation by IPO primary market investors is of great

importance. We argue that corporate hedging effectively reduces the information asymmetry of issuing companies, hence investors require lower compensation. In turn, hedging leads to a lower IPO underpricing. In this subsection, we test the relationship between corporate hedging and IPO underpricing (hypothesis H3) with the following regression:⁷

$$IPO\ Underpricing_i = \alpha + \beta * Hedging_Measure_i + \delta'X_i + \varepsilon_i$$

The *Hedging_Measures* and control variables are similar to the previous sections. In addition, we control for *Price Revision* and report the results separately to address the concern that information is incorporated into the IPO price revision. We expect the coefficients of *Hedging_Measures* to be significantly negative.

The results are reported in Table 4. Panel A presents the results without controlling for *Price Revision*, while Panel B presents the results after controlling for *Price Revision*. Our variables of interest are the overall hedging measure *Hedging*, separate hedging measures *Interest Hedging* and *FX Hedging* in columns (1)-(2), (3)-(4) and (5)-(6) correspondingly. We include year and/or industry fixed effects. The results in Panel A provide evidence that corporate hedging reduces IPO underpricing. The coefficients of hedging measures are all significantly negative at 1% level, for example, when both year and industry fixed effects are included, the underpricing of IPO firms with corporate hedging is 0.077 lower than the issuers without hedging. Using the sample mean of IPO size, the effect of corporate hedging translates into a \$16.38m reduction in money left on the table on average, which is economically significant. When *Interest Hedging* and *FX Hedging* are distinguished, *FX Hedging* shows a slightly stronger effect on reducing IPO underpricing compared to *Interest Hedging*.

⁷ In un-tabulated tests, we also include the post-IPO volatility as a control variable. The results are qualitatively similar.

[Table 4 about here]

The control variables have consistent coefficients with previous findings. For example, IPO firms listed on Nasdaq are associated with a higher level of underpricing, which is consistent with the fact that they are generally smaller and riskier than those listed on NYSE and AMEX. In addition, the venture-backed IPOs are associated with more underpricing, consistent with the grandstanding argument of Lee and Wahal (2004).

In Panel B of Table 4, when *Price Revision* is controlled, the results are qualitatively similar to Panel A. All the coefficients of corporate hedging measures are highly significantly negative, suggesting that corporate hedging is associated with lower IPO underpricing even after controlling for price revision. The magnitudes of the coefficients are now smaller, which is consistent with the intuition that part of the information is revealed through price revision. In all the specifications, the coefficients of *Price Revision* are highly significantly positive, which are consistent with the “partial adjustment” phenomenon (Hanley, 1993; Bradely Jordan, 2002).

5.2.2 Corporate hedging and post-IPO idiosyncratic volatility

We now provide related evidences that corporate hedging reduces information asymmetry of IPO firms. In this subsection, we test whether corporate hedging reduces the aftermarket idiosyncratic volatility of IPO stocks (hypothesis H4), using the following regression model:

$$Aftermarket\ Volatility_i = \alpha + \beta * Hedging_Measure_i + \delta'X_i + \varepsilon_i$$

The *Hedging_Measures* and control variables used are similar to the previous sections. In addition, we control for *Price Revision* and report the results separately. Following Beatty and Ritter (1986), we use *Aftermarket Volatility* to measure the ex post

uncertainty of IPO stocks. If corporate hedging reduces information asymmetry of the issuers, the ex-ante value uncertainty of IPO firms should be reduced. We hence expect the coefficients of hedging measures to be significantly negative.

The results are reported in Table 5. Panel A presents the results without controlling for *Price Revision*, while Panel B presents the results after controlling for *Price Revision*. Our variables of interest are *Hedging*, *Interest Hedging* and *FX Hedging* in columns (1)-(2), (3)-(4) and (5)-(6) correspondingly. In Panel A, all the coefficients of hedging measures are highly significantly negative at 1% level. For example, in column (2) when overall hedging is used and both year and industry fixed effects are included, the result shows that corporate hedging reduces the aftermarket idiosyncratic volatility by 0.031 at 1% significance level. Compared with the mean aftermarket volatility of 0.39, this effect is also economically significant. In Panel B where we also control for *Price Revision*, the results are similar.

[Table 5 about here]

5.2.3 Corporate hedging and post-IPO liquidity

If corporate hedging reduces information asymmetry of the IPO firms and extends the investor bases, we should observe issuers with corporate hedging are associated with a higher level of liquidity. Moreover, as argued by Booth and Chua (1996) that IPO underpricing is aimed to enlarge the pool of investors and gain liquidity benefit, corporate hedging can increase firm value via the channel of improving stock liquidity. In this subsection, we test the relationship between corporate hedging and post-IPO liquidity (hypothesis H5). Specifically, we run the following regression:

$$Aftermarket\ Illiquidity_i = \alpha + \beta * Hedging_Measure_i + \delta'X_i + \varepsilon_i$$

The *Hedging_Measures* and control variables used are similar to the previous sections. In addition, we control for *Price Revision* and report the results separately. Since the dependent variable is the Amihud's illiquidity measure, we expect the coefficients of hedging measures to be significantly negative.

The results are reported in Table 6. Our variables of interest are *Hedging*, *Interest Hedging* and *FX Hedging* in columns (1)-(2), (3)-(4) and (5)-(6) correspondingly. Panel A presents the results without controlling for *Price Revision*. When the overall corporate hedging is used to measure hedging activities, we find that hedging reduces the aftermarket illiquidity of IPO firms at 1% significance level. Issuers with corporate hedging have post-IPO stocks that are 0.027 (6.92% of the average illiquidity measure) more liquid than those without hedging, when year fixed effect is included. In columns (3)-(4), when only *Interest Hedging* is measured, the results are similar: IPO firms with corporate hedging are associated with higher liquidity. However, we do not find a significant relationship between *FX Hedging* and aftermarket stock illiquidity in columns (5)-(6).

[Table 6 about here]

In Panel B, we add *Price Revision* as an additional control variable. The coefficients of all hedging measure are now significantly negative. For example, when *Hedging* and *Interest Hedging* are used, the results suggest that corporate hedging reduces aftermarket illiquidity of issuers at 1% significance level. The result is weaker when *FX Hedging* is used to measure hedging activities: the coefficients are significantly negative at 10% level.

Overall, we find strong evidence that corporate hedging reduces the IPO firms' aftermarket illiquidity. However, the results for *FX Hedging* are weaker.

5.2.4 Corporate Hedging and post-IPO long-term performance

Theories suggest that long-term underperformance of IPOs is caused by heterogeneous expectations among investors about the firm's future cash flow and the cost associated with short-selling the shares of IPO stocks. If corporate hedging leads to a reduction in information asymmetry and heterogeneity among investors, the aftermarket IPO long-term performance should be higher. In this subsection, we test the relationship between corporate hedging and aftermarket long-term stock performance (hypothesis H6). Specifically, we run the following regression:

$$\text{Aftermarket IPO Performance}_i = \alpha + \beta * \text{Hedging_Measure}_i + \delta' X_i + \varepsilon_i$$

The *Hedging_Measures* and control variables used are similar to the previous sections. Year and/or industry fixed effects are added. In addition, we control for *Price Revision* and report the results separately. We expect the coefficients of hedging measures to be significantly positive.

The results are reported in Table 7. Our variables of interest are *Hedging*, *Interest Hedging* and *FX Hedging* in columns (1)-(2), (3)-(4) and (5)-(6) correspondingly. Panel A presents the results without controlling for *Price Revision*, and Panel B reports the results after controlling for *Price Revision*. All the coefficients of corporate hedging measures are highly significantly positive, suggesting that corporate hedging indeed enhances the long-term post-IPO performance. In Panel A, the coefficients of corporate hedging measures range from 0.081 to 0.104 (depending on which hedging measure is used and whether industry fixed effect is included), while in Panel B the coefficients are slightly smaller, ranging from 0.079 to 0.100. Compared to the average long-term performance of -0.11 for IPO firms, the effect of corporate hedging on aftermarket performance is huge.

[Table 7 about here]

6. Conclusion

We add to the important debate of whether corporate hedging increases firm value by studying the IPO market. We hypothesize that corporate hedging allows the investors to learn better about the management ability and project quality, hence reduces the information asymmetry between underwriters and informed investors, as well as between uninformed and informed investors. As a result, corporate hedging increases the firm value of IPOs in the issuing process. Using a sample of 2087 IPOs from 1996 to 2009, we find consistent results.

We find that issuers with corporate hedging have less information to extract from informed investors and are associated with smaller price revision and lower underwriting fee. More importantly, corporate hedging is found to reduce IPO underpricing, which provides direct evidence that corporate hedging increases firm value particularly during the issuing process. We also provide further evidence that corporate hedging increases firm value through the channel of reducing information asymmetry and value uncertainty, by documenting that corporate hedging reduces IPO aftermarket idiosyncratic volatility and enhances aftermarket liquidity and long-term performance.

References

- Allayannis, G., and J. Weston, 2001, The use of foreign currency derivatives and firm market value, *Review of Financial Studies*, 14, 243-76.
- Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time series effects, *Journal of Financial Markets*, 5, 31-56.
- Beatty, R., and J. Ritter, 1986, Investment banking, reputation, and the underpricing of initial public offerings, *Journal of Financial Economics*, 15, 213-232.
- Benveniste, L., and P. Spindt, 1989, How investment bankers determine the offer price and allocation of the new issues, *Journal of Financial Economics*, 24, 343-362.
- Benveniste, L., and W. Wilhelm, 1990, A comparative analysis of IPO proceeds under alternative regulatory environments, *Journal of Financial Economics*, 28, 173-208.
- Bessembinder, H., 1991, Forward contracts and firm value: investment incentive and contracting effects. *Journal of Financial and Quantitative Analysis*, 26, 519-532.
- Booth, J.R., and L. Chua, 1996, Ownership dispersion, costly information, and IPO underpricing, *Journal of Financial Economics*, 41(2), 291-310.
- Booth, J.R., and R. Smith, 1986, Capital raising, underwriting and the certification hypothesis, *Journal of Financial Economics*, 15, 261-281.
- Bradely, D., and B. Jordan, 2002, Partial adjustment to public information and IPO underpricing, *Journal of Financial and Quantitative Analysis*, 37, 595-616.
- Campbell, T.S., and W.A. Kracaw, 1990, Corporate risk management and incentive effects of debt, *Journal of Finance*, 45, 1673-1686.
- Campello, M., C. Lin, Y. Ma, and H. Zhou, 2011, The real and financial implications of corporate hedging, *The Journal of Finance*, 66, 1615-1647.
- Carter, D.A., A.A. Rogers, and B.J. Simkins, 2006, Does hedging affect firm value? Evidence from the U.S. airline industry, *Financial Management*, 35, 53-87.
- Carter, R.B., and S. Manaster, 1990, Initial public offerings and underwriter reputation, *Journal of Finance*, 45, 1045-1067.
- Chemmanur, T.J., and I. Paeglis, 2005, Management quality, certification, and the initial public offerings, *Journal of Financial Economics*, 76, 331-368.
- Chen, J., H. Hong, and J. Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics*, 66, 171-205.
- DaDalt, P., G.D. Gay, and J. Nam, 2002, Asymmetric information and corporate derivatives use, *Journal of Future Markets*, 22, 241-267.

- DeMarzo, P.M., and D. Duffie, 1995. Corporate incentives for hedging and hedge accounting, *Review of Financial Studies*, 8, 743-771.
- Duffie, D., N. Garleanu, and L. Pedersen, 2002, Securities lending, shorting, and pricing, *Journal of Financial Economics*, 66, 307-309.
- Froot, K., D. Scharfstein, and J. Stein, 1993, Risk management: coordinating corporate investment and financing policies, *The Journal of Finance*, 48, 1629-1658.
- Graham, J.R., and D.A. Rogers, 2002, Do firms hedge in response to tax incentives? *Journal of Finance*, 57, 815-839.
- Guay, W., and S.P. Kothari, 2003, How much do firms hedge with derivatives? *Journal of Financial Economics*, 70, 423-461.
- Hanley, K., 1993, The underpricing of initial public offerings and the partial adjustment phenomenon, *Journal of Financial Economics*, 34, 231-250.
- Hanley, K., and G. Hoberg, 2010, The information content of IPO prospectuses, *Review of Financial Studies*, 23, 2821-2864.
- Jin, Y., and P. Jorion, 2006, Firm value and hedging: Evidence from U.S. oil and gas producers, *Journal of Finance*, 66, 893-919.
- Lee, P.M., and S. Wahal, 2004, Grandstanding, certification, and the underpricing of venture capital backed IPOs, *Journal of Financial Economics*, 73, 375-407.
- Loughran, T., and B. McDonald, 2013, IPO first-day returns, offer price revisions, volatility, and form S-1 language, *Journal of Financial Economics*, 109, 307-326.
- Lowry, M., and G.W. Schwert, 2004, Is the IPO pricing process efficient? *Journal of Financial Economics*, 71, 3-26.
- Manconi A., M. Massa, and L. Zhang, 2016, The Informational Role of Corporate Hedging. *Management Science*, Forthcoming.
- Michaely, R., and W.H. Shaw, 1994, The pricing of initial public offerings: tests of adverse-selection and signalling theories, *Review of Financial Studies*, 7, 279-319.
- Modigliani, F., and M.H. Miller, 1958, The cost of capital, corporation finance and the theory of investment, *American Economic Review*, 48, 261-297.
- Morris, S., 1996, Speculative investor behaviour and learning, *Quarterly Journal of Economics*, 111, 1111-1133.
- Perez-Gonzalez, F., and H. Yun, 2013, Risk management and firm value: evidence from weather derivatives, *The Journal of Finance*, 68, 2143-2176.
- Purnanandam, A., 2008, Financial distress and corporate risk management: theory and evidence, *Journal of Financial Economics*, 87, 706-739.

- Ritter, J.R., 1984, The hot issue market of 1980, *Journal of Business*, 57, 215-240.
- Rock, K., 1986, Why new issues are underpriced, *Journal of Financial Economics*, 15, 187-212.
- Sherman, A., and S. Titman, 2002, Building the IPO order book: underpricing and participation limits with costly information, *Journal of Financial Economics*, 65, 3-29.
- Smith, C.W., and R.M. Stulz, 1985, The determinants of firms' hedging policies, *Journal of Financial and Quantitative Analysis*, 20, 391-405.
- Spatt, C., and S. Srivastava, 1991, Preplay communication, participation restrictions, and efficiency in initial public offerings, *Review of Financial Studies*, 4, 709-726.
- Stulz, R., 1984, Optimal hedging policies, *Journal of Financial and Quantitative Analysis*, 19, 2, 127-140.
- Titman, S., and B. Trueman, 1986, Information quality and the valuation of new issues, *Journal of Accounting and Economics*, 8, 159-172.
- Tufano, P., 1996, Who manages risk? An empirical examination of risk management practices in the gold mining industry, *Journal of Finance*, 51, 1097-1137

Table 1: Summary Statistics

Panel A summarizes the main variables used in our study. The sample all the US firms that went public between 1996 and 2009, with the exclusions 1) unit offers, REITs, ADRs and deals with offer price below five dollars; 2) financial IPO firms with SIC codes from 6000 to 6999; 3) IPO firms that miss important control variables for our analysis; 4) IPO firms that are not covered by Center for Research in Security Prices (CRSP) database. In Panel B, we also split the sample into industries based on Fama-French 12 industry classification, and summarize the hedging information.

Panel A: Summary Statistics of Main Variables

Variables	Mean	Median	Std. Dev.	N
Hedging	0.28	0.00	0.45	2087
Interest Hedging	0.24	0.00	0.43	2087
FX Hedging	0.10	0.00	0.30	2087
Firm Age before IPO	2.24	2.20	0.96	2087
IPO Size	5.36	5.38	1.08	2087
Bond Outstanding Dummy	0.03	0.00	0.17	2087
Nasdaq Dummy	0.77	1.00	0.42	2087
High Tech Industry Dummy	0.63	1.00	0.48	2087
Financial Center	0.34	0.00	0.47	2087
Insider Ownership	0.44	0.48	0.38	2087
Insider Ownership Missing Dummy	0.29	0.00	0.45	2087
Lockup Period	3.97	5.20	2.24	2087
Venture-capital Backed Dummy	0.48	0.00	0.50	2087
High Ranked Underwriter Dummy	0.44	0.00	0.50	2087
Number of Underwriters	1.17	1.00	0.47	2087
Star-analyst Coverage Dummy	0.20	0.00	0.40	2087
Recent Market Returns	0.02	0.02	0.04	2087
Recent Market-average IPO Premium	0.29	0.18	0.27	2087
Recent Market IPO Volume	8.55	8.52	0.61	2087
IPO Underwriting Fee	6.97	7.00	0.54	1805
IPO Price Revision	-0.01	0.00	0.24	2087
IPO Underpricing	0.25	0.12	0.39	2087
After-market Idiosyncratic Volatility	0.39	0.36	0.15	2047
After-market Amihud Illiquidity	0.17	0.12	0.14	2047
After-Market IPO Performance: 1-Year	-0.11	-0.20	0.52	2087

Panel B: Corporate Hedging of IPO Firms by Industry

<i>Fama-French 12 Industry Classification</i>	Hedge		Interest Hedge		FX Hedge		N
	Mean	Std.	Mean	Std.	Mean	Std.	
Consumer NonDurables	0.39	0.49	0.35	0.48	0.09	0.29	74
Consumer Durables	0.51	0.51	0.40	0.50	0.29	0.46	35
Manufacturing	0.52	0.50	0.46	0.50	0.17	0.37	108
Oil, Gas, and Coal Extraction and Production	0.49	0.50	0.44	0.50	0.17	0.38	59
Chemicals and Allied Products	0.46	0.51	0.39	0.50	0.32	0.48	28
Business Equipment	0.18	0.38	0.13	0.34	0.09	0.29	748
Telephone and Television Transmission	0.46	0.50	0.46	0.50	0.10	0.31	125
Utilities	0.63	0.50	0.58	0.51	0.37	0.50	19
Wholesale, Retail Services	0.35	0.48	0.32	0.47	0.11	0.31	202
Healthcare, Medical Equipment, and Drug	0.14	0.35	0.11	0.32	0.05	0.22	331
Other -- Mines, Construction, etc.	0.32	0.47	0.31	0.46	0.08	0.27	356

Table 2: Hedging and IPO Price Revision

In this table, we test the relationship between IPO price revision and corporate hedging (hypothesis H1), we run the following regression:

$$IPO\ Price\ Revision_i = \alpha + \beta * Hedging_Measure_i + \delta'X_i + \varepsilon_i$$

For *Hedging_Measures* we use are three sets of dummy variables *Hedging_i*, *Interest Hedging_i* and *FX Hedging_i*. *X_i* is a set of control variables. In Columns (1)-(2), the variable of interest is the dummy variable *Hedging*, where we do not distinguish between types of financial derivatives. We then separate *Hedging* to interest rate risk hedging and foreign exchange rate risk hedging, and reports the results in column (3)-(4) and column (5)-(6) respectively. We first include only year fixed effect and then include both year and industry fixed effects. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	-0.036*** (-3.31)	-0.039*** (-3.59)				
Interest Hedging			-0.031*** (-2.87)	-0.034*** (-3.08)		
FX Hedging					-0.063*** (-3.79)	-0.068*** (-4.14)
Firm Age before IPO	-0.011** (-2.19)	-0.014*** (-2.74)	-0.012** (-2.32)	-0.015*** (-2.87)	-0.010** (-2.13)	-0.014*** (-2.71)
IPO Size	0.097*** (13.85)	0.093*** (13.37)	0.096*** (13.78)	0.092*** (13.30)	0.097*** (13.94)	0.093*** (13.40)
Bond Outstanding Dummy	-0.083*** (-3.33)	-0.058** (-2.31)	-0.083*** (-3.34)	-0.058** (-2.29)	-0.089*** (-3.62)	-0.064*** (-2.59)
Nasdaq Dummy	0.023* (1.82)	0.022* (1.73)	0.023* (1.86)	0.022* (1.76)	0.022* (1.77)	0.021* (1.70)
High Tech Industry Dummy	-0.009 (-0.89)	0.019 (1.41)	-0.009 (-0.86)	0.019 (1.45)	-0.005 (-0.50)	0.023* (1.73)
Financial Center	0.010 (0.91)	0.002 (0.18)	0.010 (0.93)	0.002 (0.19)	0.011 (1.03)	0.003 (0.26)
Insider Ownership	0.019 (1.12)	0.013 (0.76)	0.019 (1.13)	0.013 (0.77)	0.018 (1.07)	0.012 (0.69)
Insider Ownership Missing Dummy	0.016 (0.85)	0.012 (0.65)	0.015 (0.82)	0.011 (0.62)	0.016 (0.86)	0.012 (0.66)
Lockup Period	-0.003 (-0.75)	-0.003 (-0.84)	-0.003 (-0.77)	-0.003 (-0.86)	-0.003 (-0.76)	-0.003 (-0.85)
Venture-capital Backed Dummy	-0.024** (-2.10)	-0.011 (-0.99)	-0.023** (-2.03)	-0.011 (-0.95)	-0.022** (-2.01)	-0.010 (-0.89)
High Ranked Underwriter Dummy	-0.002 (-0.20)	-0.003 (-0.26)	-0.002 (-0.17)	-0.003 (-0.21)	-0.004 (-0.34)	-0.004 (-0.38)
Number of Underwriters	-0.030** (-2.43)	-0.029** (-2.44)	-0.029** (-2.39)	-0.028** (-2.38)	-0.026** (-2.14)	-0.025** (-2.13)
Star-analyst Coverage Dummy	-0.006 (-0.47)	-0.006 (-0.48)	-0.006 (-0.50)	-0.006 (-0.51)	-0.007 (-0.56)	-0.007 (-0.58)
Recent Market Returns	1.023*** (7.25)	1.093*** (7.91)	1.026*** (7.28)	1.098*** (7.96)	1.028*** (7.34)	1.098*** (8.00)
Recent Market-average IPO Premium	0.243*** (7.10)	0.232*** (6.96)	0.243*** (7.05)	0.230*** (6.90)	0.242*** (7.00)	0.230*** (6.88)
Recent Market IPO Volume	-0.022** (-2.45)	-0.021** (-2.39)	-0.021** (-2.44)	-0.021** (-2.38)	-0.021** (-2.40)	-0.021** (-2.34)
Quality	0.004 (0.54)	0.004 (0.51)	0.004 (0.55)	0.004 (0.51)	0.004 (0.55)	0.004 (0.54)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	-	Y	-	Y	-	Y
Number of Observations	2,084	2,082	2,084	2,082	2,084	2,082
R-squared	0.251	0.310	0.250	0.309	0.253	0.312

Table 3: Hedging and Underwriting Fee

In this table, we test the relationship between underwriting fee and corporate hedging (hypothesis H2), we run the following regression:

$$\text{Underwriting Fee}_i = \alpha + \beta * \text{Hedging_Measure}_i + \delta' X_i + \varepsilon_i$$

For *Hedging_Measures* we use are three sets of dummy variables *Hedging_i*, *Interest Hedging_i* and *FX Hedging_i*. *X_i* is a set of control variables. In Columns (1)-(2), the variable of interest is the dummy variable *Hedging*, where we do not distinguish between types of financial derivatives. We then separate *Hedging* to interest rate risk hedging and foreign exchange rate risk hedging, and reports the results in column (3)-(4) and column (5)-(6) respectively. We first include only year fixed effect and then include both year and industry fixed effects. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	-0.103*** (-4.11)	-0.100*** (-3.95)				
Interest Hedging			-0.102*** (-3.82)	-0.096*** (-3.62)		
FX Hedging					-0.111*** (-2.68)	-0.101** (-2.33)
Firm Age before IPO	-0.067*** (-5.21)	-0.071*** (-5.33)	-0.069*** (-5.33)	-0.072*** (-5.44)	-0.069*** (-5.33)	-0.073*** (-5.48)
IPO Size	-0.318*** (-13.32)	-0.319*** (-13.20)	-0.320*** (-13.42)	-0.321*** (-13.29)	-0.321*** (-13.16)	-0.321*** (-13.05)
Bond Outstanding Dummy	-0.113* (-1.84)	-0.075 (-1.16)	-0.112* (-1.85)	-0.073 (-1.13)	-0.134** (-2.19)	-0.093 (-1.43)
Nasdaq Dummy	-0.114*** (-2.61)	-0.113** (-2.54)	-0.112** (-2.56)	-0.112** (-2.50)	-0.108** (-2.50)	-0.107** (-2.43)
High Tech Industry Dummy	0.002 (0.06)	-0.029 (-0.84)	0.002 (0.06)	-0.029 (-0.83)	0.012 (0.44)	-0.022 (-0.62)
Financial Center	0.051** (2.26)	0.027 (1.17)	0.051** (2.28)	0.028 (1.19)	0.055** (2.45)	0.030 (1.30)
Insider Ownership	0.047 (1.18)	0.037 (0.89)	0.049 (1.22)	0.038 (0.93)	0.042 (1.06)	0.030 (0.72)
Insider Ownership Missing Dummy	-0.024 (-0.49)	-0.030 (-0.63)	-0.025 (-0.52)	-0.031 (-0.66)	-0.026 (-0.53)	-0.032 (-0.68)
Lockup Period	0.001 (0.09)	-0.003 (-0.29)	0.001 (0.07)	-0.003 (-0.31)	0.001 (0.07)	-0.003 (-0.28)
Venture-capital Backed Dummy	0.014 (0.63)	0.026 (1.13)	0.015 (0.69)	0.026 (1.15)	0.020 (0.90)	0.030 (1.34)
High Ranked Underwriter Dummy	0.005 (0.26)	-0.004 (-0.22)	0.007 (0.36)	-0.003 (-0.12)	0.001 (0.03)	-0.007 (-0.36)
Number of Underwriters	-0.200*** (-5.35)	-0.195*** (-4.93)	-0.199*** (-5.26)	-0.193*** (-4.83)	-0.196*** (-5.34)	-0.193*** (-4.87)
Star-analyst Coverage Dummy	0.018 (0.79)	0.025 (1.07)	0.017 (0.75)	0.024 (1.05)	0.017 (0.75)	0.023 (1.01)
Recent Market Returns	-0.169 (-0.59)	-0.153 (-0.54)	-0.169 (-0.59)	-0.147 (-0.52)	-0.144 (-0.50)	-0.125 (-0.44)
Recent Market-average IPO Premium	0.042 (0.82)	0.033 (0.65)	0.040 (0.77)	0.030 (0.59)	0.037 (0.72)	0.028 (0.57)
Recent Market IPO Volume	0.013 (0.68)	0.013 (0.72)	0.013 (0.70)	0.014 (0.74)	0.015 (0.82)	0.016 (0.85)
Quality	-0.011 (-0.64)	-0.015 (-0.92)	-0.010 (-0.61)	-0.014 (-0.91)	-0.011 (-0.64)	-0.014 (-0.90)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	-	Y	-	Y	-	Y
Number of Observations	1,802	1,800	1,802	1,800	1,802	1,800
R-squared	0.383	0.417	0.382	0.416	0.381	0.415

Table 4: Hedging and IPO Underpricing

In this table, we test the relationship between IPO underpricing and corporate hedging (hypothesis H3), we run the following regression:

$$IPO\ Underpricing_i = \alpha + \beta * Hedging_Measure_i + \delta'X_i + \varepsilon_i$$

For *Hedging Measures* we use are three sets of dummy variables *Hedging_i*, *Interest Hedging_i* and *FX Hedging_i*. *X_i* is a set of control variables. In Panel A we do not control for price revision and in Panel B we include price revision. In Columns (1)-(2), the variable of interest is the dummy variable *Hedging*, where we do not distinguish between types of financial derivatives. We then separate *Hedging* to interest rate risk hedging and foreign exchange rate risk hedging, and reports the results in column (3)-(4) and column (5)-(6) respectively. We first include only year fixed effect and then include both year and industry fixed effects. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel A: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	-0.073*** (-4.46)	-0.077*** (-4.50)				
Interest Hedging			-0.067*** (-4.11)	-0.068*** (-4.04)		
FX Hedging					-0.079*** (-3.51)	-0.087*** (-3.65)
Firm Age before IPO	-0.023*** (-3.49)	-0.027*** (-3.79)	-0.025*** (-3.70)	-0.028*** (-3.98)	-0.025*** (-3.67)	-0.028*** (-3.95)
IPO Size	0.080*** (8.29)	0.076*** (7.63)	0.079*** (8.08)	0.074*** (7.40)	0.078*** (8.15)	0.074*** (7.50)
Bond Outstanding Dummy	-0.136*** (-3.64)	-0.107*** (-2.63)	-0.136*** (-3.61)	-0.106*** (-2.60)	-0.151*** (-4.05)	-0.118*** (-2.96)
Nasdaq Dummy	0.058*** (3.64)	0.053*** (3.26)	0.059*** (3.68)	0.054*** (3.28)	0.060*** (3.74)	0.055*** (3.35)
High Tech Industry Dummy	0.021 (1.44)	0.033 (1.43)	0.021 (1.46)	0.034 (1.46)	0.029** (2.05)	0.041* (1.78)
Financial Center	0.031* (1.80)	0.021 (1.20)	0.031* (1.81)	0.021 (1.21)	0.034** (1.98)	0.023 (1.32)
Insider Ownership	-0.012 (-0.43)	-0.019 (-0.61)	-0.012 (-0.42)	-0.018 (-0.61)	-0.015 (-0.51)	-0.022 (-0.71)
Insider Ownership Missing Dummy	0.003 (0.10)	-0.001 (-0.03)	0.002 (0.07)	-0.002 (-0.06)	0.003 (0.09)	-0.002 (-0.05)
Lockup Period	-0.006 (-1.02)	-0.007 (-1.18)	-0.006 (-1.05)	-0.007 (-1.20)	-0.006 (-1.05)	-0.007 (-1.19)
Venture-capital Backed Dummy	0.040** (2.32)	0.057*** (3.14)	0.041** (2.38)	0.057*** (3.16)	0.045*** (2.60)	0.061*** (3.35)
High Ranked Underwriter Dummy	0.010 (0.56)	0.009 (0.48)	0.011 (0.62)	0.010 (0.53)	0.007 (0.39)	0.006 (0.34)
Number of Underwriters	-0.022 (-1.54)	-0.022 (-1.46)	-0.021 (-1.47)	-0.021 (-1.39)	-0.019 (-1.30)	-0.018 (-1.19)
Star-analyst Coverage Dummy	0.023 (1.02)	0.022 (1.00)	0.022 (0.98)	0.022 (0.96)	0.021 (0.94)	0.021 (0.91)
Recent Market Returns	0.327 (1.40)	0.405* (1.72)	0.331 (1.42)	0.414* (1.76)	0.347 (1.49)	0.425* (1.81)
Recent Market-average IPO Premium	0.326*** (4.25)	0.318*** (4.16)	0.325*** (4.21)	0.315*** (4.11)	0.322*** (4.19)	0.315*** (4.11)
Recent Market IPO Volume	-0.020 (-1.46)	-0.019 (-1.38)	-0.020 (-1.45)	-0.019 (-1.37)	-0.019 (-1.40)	-0.018 (-1.32)
Quality	-0.024** (-2.57)	-0.026*** (-2.81)	-0.024** (-2.55)	-0.026*** (-2.81)	-0.024** (-2.56)	-0.026*** (-2.78)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	-	Y	-	Y	-	Y
Number of Observations	2,084	2,082	2,084	2,082	2,084	2,082
R-squared	0.274	0.308	0.273	0.306	0.272	0.306

Panel B: Control for Price Revision

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	-0.046*** (-3.241)	-0.048*** (-3.194)				
Interest Hedging			-0.043*** (-3.02)	-0.043*** (-2.88)		
FX Hedging					-0.014** (-2.33)	-0.015** (-2.46)
Price Revision	0.758*** (19.53)	0.728*** (18.49)	0.760*** (19.53)	0.730*** (18.50)	0.761*** (19.43)	0.730*** (18.39)
Same Specifications as in Panel A	Y	Y	Y	Y	Y	Y

Table 5: Hedging and After-Market Stock Idiosyncratic Volatility

In this table, we test the relationship between IPO aftermarket stock idiosyncratic volatility and corporate hedging (hypothesis H4), we run the following regression:

$$\text{Aftermarket volatility}_i = \alpha + \beta * \text{Hedging_Measure}_i + \delta' X_i + \varepsilon_i$$

For *Hedging Measures* we use are three sets of dummy variables *Hedging_i*, *Interest Hedging_i* and *FX Hedging_i*. *X_i* is a set of control variables. In Panel A we do not control for price revision and in Panel B we include price revision. In Columns (1)-(2), the variable of interest is the dummy variable *Hedging*, where we do not distinguish between types of financial derivatives. We then separate *Hedging* to interest rate risk hedging and foreign exchange rate risk hedging, and reports the results in column (3)-(4) and column (5)-(6) respectively. We first include only year fixed effect and then include both year and industry fixed effects. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel A: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	-0.030*** (-6.414)	-0.031*** (-6.508)				
Interest Hedging			-0.032*** (-6.48)	-0.031*** (-6.37)		
FX Hedging					-0.016*** (-2.783)	-0.017*** (-2.804)
Firm Age before IPO	-0.012*** (-5.33)	-0.013*** (-5.78)	-0.012*** (-5.49)	-0.013*** (-5.92)	-0.013*** (-5.88)	-0.014*** (-6.29)
IPO Size	0.001 (0.34)	-0.000 (-0.17)	0.001 (0.26)	-0.001 (-0.29)	-0.001 (-0.36)	-0.002 (-0.83)
Bond Outstanding Dummy	-0.035*** (-3.36)	-0.028*** (-2.59)	-0.034*** (-3.23)	-0.027** (-2.46)	-0.042*** (-3.92)	-0.033*** (-2.96)
Nasdaq Dummy	0.028*** (5.07)	0.024*** (4.42)	0.028*** (5.06)	0.024*** (4.40)	0.030*** (5.35)	0.026*** (4.67)
High Tech Industry Dummy	0.045*** (9.44)	0.036*** (5.62)	0.044*** (9.35)	0.036*** (5.61)	0.048*** (10.15)	0.039*** (6.00)
Financial Center	0.013*** (2.98)	0.010** (2.35)	0.012*** (2.94)	0.010** (2.34)	0.014*** (3.31)	0.011*** (2.59)
Insider Ownership	-0.006 (-0.80)	-0.010 (-1.27)	-0.006 (-0.75)	-0.009 (-1.23)	-0.007 (-0.95)	-0.012 (-1.48)
Insider Ownership Missing Dummy	-0.007 (-0.98)	-0.009 (-1.23)	-0.007 (-1.02)	-0.009 (-1.27)	-0.008 (-1.05)	-0.010 (-1.31)
Lockup Period	0.000 (0.12)	-0.000 (-0.24)	0.000 (0.10)	-0.000 (-0.26)	0.000 (0.07)	-0.000 (-0.27)
Venture-capital Backed Dummy	0.018*** (4.07)	0.021*** (4.70)	0.018*** (4.08)	0.021*** (4.68)	0.021*** (4.61)	0.024*** (5.14)
High Ranked Underwriter Dummy	-0.003 (-0.57)	-0.005 (-1.05)	-0.002 (-0.45)	-0.004 (-0.95)	-0.004 (-0.84)	-0.006 (-1.25)
Number of Underwriters	0.007* (1.90)	0.009** (2.11)	0.008** (2.03)	0.009** (2.24)	0.007* (1.81)	0.008** (2.04)
Star-analyst Coverage Dummy	-0.007 (-1.48)	-0.005 (-0.92)	-0.008 (-1.56)	-0.005 (-0.99)	-0.008 (-1.54)	-0.005 (-0.96)
Recent Market Returns	-0.245*** (-4.52)	-0.231*** (-4.31)	-0.245*** (-4.52)	-0.229*** (-4.28)	-0.233*** (-4.26)	-0.218*** (-4.02)
Recent Market-average IPO Premium	0.034** (2.50)	0.032** (2.37)	0.034** (2.46)	0.031** (2.29)	0.032** (2.31)	0.029** (2.16)
Recent Market IPO Volume	0.013*** (3.69)	0.013*** (3.79)	0.013*** (3.64)	0.013*** (3.74)	0.013*** (3.77)	0.014*** (3.86)
Quality	-0.009*** (-3.01)	-0.009*** (-3.34)	-0.008*** (-3.01)	-0.009*** (-3.37)	-0.009*** (-2.98)	-0.009*** (-3.28)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	-	Y	-	Y	-	Y
Number of Observations	2,044	2,042	2,044	2,042	2,044	2,042
R-squared	0.672	0.690	0.671	0.689	0.666	0.684

Panel B: Control For Price Revision

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	-0.029*** (-6.10)	-0.030*** (-6.26)				
Interest Hedging			-0.030*** (-6.19)	-0.030*** (-6.14)		
FX Hedging					-0.014** (-2.33)	-0.015** (-2.46)
Price Revision	0.042*** (4.73)	0.028*** (3.11)	0.043*** (4.76)	0.029*** (3.17)	0.045*** (4.91)	0.031*** (3.34)
Same Specifications as in Panel A	Y	Y	Y	Y	Y	Y

Table 6: Hedging and Aftermarket Illiquidity

In this table, we test the relationship between IPO aftermarket illiquidity and corporate hedging (hypothesis H5), we run the following regression:

$$\text{Aftermarket Illiquidity}_i = \alpha + \beta * \text{Hedging_Measure}_i + \delta' X_i + \varepsilon_i$$

For *Hedging Measures* we use are three sets of dummy variables *Hedging_i*, *Interest Hedging_i* and *FX Hedging_i*. *X_i* is a set of control variables. In Panel A we do not control for price revision and in Panel B we include price revision. In Columns (1)-(2), the variable of interest is the dummy variable *Hedging*, where we do not distinguish between types of financial derivatives. We then separate *Hedging* to interest rate risk hedging and foreign exchange rate risk hedging, and reports the results in column (3)-(4) and column (5)-(6) respectively. We first include only year fixed effect and then include both year and industry fixed effects. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel A: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	-0.027*** (-3.99)	-0.021*** (-2.97)				
Interest Hedging			-0.028*** (-3.95)	-0.022*** (-2.99)		
FX Hedging					-0.007 (-0.84)	-0.002 (-0.25)
Firm Age before IPO	-0.006 (-1.36)	-0.007 (-1.59)	-0.006 (-1.45)	-0.007 (-1.64)	-0.007* (-1.69)	-0.008* (-1.86)
IPO Size	-0.118*** (-21.19)	-0.116*** (-20.29)	-0.119*** (-21.20)	-0.116*** (-20.29)	-0.120*** (-21.30)	-0.118*** (-20.37)
Bond Outstanding Dummy	0.019 (1.29)	0.011 (0.76)	0.019 (1.35)	0.012 (0.83)	0.013 (0.87)	0.008 (0.53)
Nasdaq Dummy	-0.037*** (-3.76)	-0.036*** (-3.50)	-0.037*** (-3.77)	-0.036*** (-3.52)	-0.035*** (-3.55)	-0.034*** (-3.34)
High Tech Industry Dummy	0.013 (1.47)	-0.004 (-0.31)	0.012 (1.43)	-0.004 (-0.33)	0.016* (1.82)	-0.002 (-0.13)
Financial Center	-0.003 (-0.37)	-0.003 (-0.33)	-0.003 (-0.39)	-0.003 (-0.35)	-0.001 (-0.19)	-0.002 (-0.22)
Insider Ownership	-0.020 (-1.49)	-0.017 (-1.24)	-0.020 (-1.46)	-0.017 (-1.22)	-0.021 (-1.55)	-0.018 (-1.33)
Insider Ownership Missing Dummy	-0.036*** (-2.91)	-0.033*** (-2.75)	-0.036*** (-2.95)	-0.034*** (-2.78)	-0.036*** (-2.93)	-0.034*** (-2.77)
Lockup Period	-0.002 (-0.95)	-0.003 (-1.03)	-0.003 (-0.97)	-0.003 (-1.05)	-0.003 (-0.97)	-0.003 (-1.04)
Venture-capital Backed Dummy	0.010 (1.13)	0.000 (0.00)	0.010 (1.15)	-0.000 (-0.01)	0.012 (1.46)	0.002 (0.22)
High Ranked Underwriter Dummy	-0.022*** (-2.80)	-0.021*** (-2.70)	-0.022*** (-2.72)	-0.021*** (-2.64)	-0.023*** (-2.90)	-0.022*** (-2.75)
Number of Underwriters	-0.003 (-0.43)	0.002 (0.23)	-0.003 (-0.36)	0.002 (0.30)	-0.004 (-0.53)	0.001 (0.14)
Star-analyst Coverage Dummy	0.001 (0.20)	0.001 (0.21)	0.001 (0.15)	0.001 (0.18)	0.001 (0.14)	0.001 (0.18)
Recent Market Returns	-0.106 (-1.15)	-0.125 (-1.35)	-0.106 (-1.15)	-0.124 (-1.35)	-0.095 (-1.03)	-0.115 (-1.25)
Recent Market-average IPO Premium	-0.029 (-1.53)	-0.023 (-1.24)	-0.029 (-1.55)	-0.024 (-1.27)	-0.030 (-1.62)	-0.025 (-1.32)
Recent Market IPO Volume	0.023*** (3.64)	0.023*** (3.56)	0.023*** (3.63)	0.023*** (3.55)	0.023*** (3.69)	0.023*** (3.60)
Quality	0.008 (1.404)	0.008 (1.513)	0.008 (1.410)	0.008 (1.507)	0.008 (1.407)	0.008 (1.520)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	-	Y	-	Y	-	Y
Number of Observations	2,044	2,042	2,044	2,042	2,044	2,042
R-squared	0.458	0.485	0.458	0.485	0.456	0.483

Panel B: Control For Price Revision

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	-0.034*** (-5.10)	-0.028*** (-3.99)				
Interest Hedging			-0.033*** (-4.91)	-0.028*** (-3.85)		
FX Hedging					-0.018** (-2.31)	-0.013* (-1.65)
Price Revision	-0.200*** (-9.90)	-0.183*** (-8.86)	-0.200*** (-9.84)	-0.182*** (-8.81)	-0.198*** (-9.76)	-0.181*** (-8.72)
Same Specifications as in Panel A	Y	Y	Y	Y	Y	Y

Table 7: Hedging and After-Market IPO Performance

In this table, we test the relationship between after-market IPO performance and corporate hedging (hypothesis H6), we run the following regression:

$$\text{Aftermarket IPO performance}_i = \alpha + \beta * \text{Hedging_Measure}_i + \delta' X_i + \varepsilon_i$$

For *Hedging_Measures* we use are three sets of dummy variables *Hedging_i*, *Interest Hedging_i* and *FX Hedging_i*. *X_i* is a set of control variables. In Panel A we do not control for price revision and in Panel B we include price revision. In Columns (1)-(2), the variable of interest is the dummy variable *Hedging*, where we do not distinguish between types of financial derivatives. We then separate *Hedging* to interest rate risk hedging and foreign exchange rate risk hedging, and reports the results in column (3)-(4) and column (5)-(6) respectively. We first include only year fixed effect and then include both year and industry fixed effects. t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel A: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	0.091*** (3.24)	0.104*** (3.64)				
Interest Hedging			0.081*** (2.92)	0.097*** (3.38)		
FX Hedging					0.093** (2.28)	0.096** (2.35)
Firm Age before IPO	0.026** (2.13)	0.035*** (2.72)	0.028** (2.27)	0.036*** (2.84)	0.028** (2.28)	0.037*** (2.93)
IPO Size	0.038*** (2.85)	0.034** (2.44)	0.040*** (3.01)	0.035*** (2.59)	0.041*** (3.08)	0.038*** (2.71)
Bond Outstanding Dummy	0.053 (0.74)	0.109 (1.46)	0.053 (0.74)	0.107 (1.44)	0.071 (0.98)	0.125* (1.66)
Nasdaq Dummy	0.072*** (2.60)	0.057** (1.97)	0.071** (2.57)	0.057** (1.97)	0.069** (2.49)	0.053* (1.84)
High Tech Industry Dummy	0.049* (1.95)	0.020 (0.59)	0.049* (1.94)	0.019 (0.58)	0.039 (1.55)	0.009 (0.26)
Financial Center	-0.027 (-1.12)	-0.022 (-0.89)	-0.027 (-1.13)	-0.023 (-0.90)	-0.031 (-1.29)	-0.026 (-1.03)
Insider Ownership	0.066 (1.37)	0.056 (1.13)	0.065 (1.36)	0.056 (1.12)	0.069 (1.43)	0.061 (1.22)
Insider Ownership Missing Dummy	-0.027 (-0.57)	-0.034 (-0.71)	-0.025 (-0.54)	-0.032 (-0.69)	-0.026 (-0.55)	-0.033 (-0.69)
Lockup Period	-0.022*** (-2.64)	-0.024*** (-2.91)	-0.022*** (-2.62)	-0.024*** (-2.89)	-0.022*** (-2.61)	-0.024*** (-2.87)
Venture-capital Backed Dummy	-0.060** (-2.18)	-0.058** (-2.08)	-0.061** (-2.25)	-0.059** (-2.11)	-0.066** (-2.43)	-0.064** (-2.32)
High Ranked Underwriter Dummy	0.016 (0.55)	0.019 (0.63)	0.015 (0.51)	0.017 (0.58)	0.019 (0.68)	0.022 (0.74)
Number of Underwriters	-0.025 (-1.02)	-0.026 (-1.05)	-0.026 (-1.06)	-0.027 (-1.12)	-0.028 (-1.14)	-0.029 (-1.16)
Star-analyst Coverage Dummy	0.006 (0.20)	0.010 (0.31)	0.008 (0.24)	0.011 (0.34)	0.008 (0.27)	0.012 (0.38)
Recent Market Returns	-0.258 (-0.84)	-0.199 (-0.64)	-0.263 (-0.86)	-0.208 (-0.67)	-0.284 (-0.93)	-0.231 (-0.74)
Recent Market-average IPO Premium	-0.251*** (-3.24)	-0.239*** (-3.07)	-0.249*** (-3.20)	-0.235*** (-3.01)	-0.246*** (-3.18)	-0.234*** (-3.00)
Recent Market IPO Volume	-0.040* (-1.85)	-0.040* (-1.84)	-0.040* (-1.85)	-0.040* (-1.84)	-0.041* (-1.91)	-0.041* (-1.89)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	-	Y	-	Y	-	Y
Number of Observations	2,084	2,082	2,084	2,082	2,084	2,082
R-squared	0.057	0.083	0.056	0.081	0.055	0.079

Panel B: Control For Price Revision

	(1)	(2)	(3)	(4)	(5)	(6)
Hedging	0.087***	0.100***				
	(3.09)	(3.48)				
Interest Hedging			0.079***	0.094***		
			(2.80)	(3.24)		
FX Hedging					0.087**	0.089**
					(2.12)	(2.17)
Price Revision	-0.095*	-0.101*	-0.098*	-0.104*	-0.096*	-0.103*
	(-1.70)	(-1.72)	(-1.76)	(-1.79)	(-1.71)	(-1.77)
Same Specifications as in Panel A	Y	Y	Y	Y	Y	Y