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Essays In Corporate Finance

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Abstract

This dissertation studies two questions in corporate finance: 1) Does knowledge sharing affect innovation? and 2) How do profit sharing and loss sharing affect the choice of underwriting fees and offer prices in the IPO market?

In the first chapter, I investigate the impact of knowledge sharing on innovation using the staggered adoption of the Uniform Trade Secrets Act as a plausibly exogenous source of variation in inter-firm information flow. I find that innovation becomes less efficient when information is more fragmented. To overcome the problem of limited informal knowledge exchange, companies are more likely to acquire technology in strategic alliances or through merger and acquisitions. I argue that the decrease in innovation is unlikely to be a result of substitution from patenting to ``padlocking" by showing that when information flow is more restricted in a state, the innovation level of companies in that state is not affected; but that of the competitors of firms in that state declines.

In the second chapter, we model share flotation, starting with the standard contract that assigns all profits above the offer price to investors, and all losses below to the underwriter. We then add profit and loss sharing to the model, and allow the issuer to set the fee and the underwriter to set the price in the initial public offerings market. However, participants deviate in practice, such that investors share some of their profits, and some of the underwriter's losses. We find that profit sharing transfers wealth from issuers to underwriters without affecting the offer price, whereas loss sharing makes both the issuer and underwriter better off, while increasing the offer price. Empirical estimation indicates minimal profit sharing but substantial loss sharing.

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ABSTRACT

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This dissertation studies two questions in corporate finance: 1) Does knowledge sharing affect innovation? and 2) How do profit sharing and loss sharing affect the choice of underwriting fees and offer prices in the IPO market?

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

CHAPTER 1 : Knowledge Sharing and Innovation

1.1. Introduction

The steam engine is widely recognized as one of the most important inventions that drove the Industrial Revolution. In 1698, Thomas Savery invented the first modern steam engine which he described as "Machine for Raising Water by Fire". He published this invention four years later. The first known working model of steam engine emerged about a decade after that in 1712 when Thomas Newcomen refined James Savery's design. In the coming years, inventors, engineers, and industrialists continued to make improvements on the previous designs and soon steam engines were driving ships and powering factories. Few know that the very first steam engine actually appeared almost 1700 years earlier in the first century AD. It was called the aeolipile at that time and was invented by Heron of Alexandria in modern day Egypt. Unfortunately, it was viewed as a mere curiosity and used only as a toy at that time. The idea never spread beyond the region and it became forgotten soon afterward. While it is not entirely fair to compare two drastically different eras, it might be worth contemplating why the invention did not catch fire the first time round during the Hellenistic period. Among many forces, the ease of knowledge transfer could be a deciding factor. Richart Trevithick decided not to patent his new high-pressure engine that he developed in 1812 and made it available for all. A group of mine managers founded the monthly journal *Leans Engine Reporter* that publishes improved engine designs "with the explicit intention of aiding the rapid diffusion of best practices among these competing firms (von Hippel and von Krogh, 2006)". Had Heron's aeolipile reached a broader audience, our history could possibly be rewritten.

Knowledge transfer is crucial to innovation in several aspects. First, new ideas are often generated by combining existing ones. For instance, the locomotive is essentially a union of the steam engine and wagonways intended for horse-drawn traffic. Second, many innovations are built upon previous work. In 1765, James Watt was about to revolutionize the steam engine when he added a separate condenser to the original design. However, his improved design had to stay on paper for a decade because before John Wilkinson invented a new boring technology in 1774 no one was able to accurately make the newly designed steam engine. Moreover, knowledge transfer can reduce duplicative efforts. If an innovation requires trying out numerous designs, knowing the failed trials by others can prevent valuable resources from being wasted on repeated futile experiments.

However, the recent trend in policy-making is toward information protection. Daniel H. Marti, who is the Intellectual Property Enforcement Coordinator at the Executive Office of the President, comments in "U.S. Joint Strategic Plan on Intellectual Property Enforcement FY 2017-2019"[1] that

> *"The protection of intellectual property rights is about promoting economic prosperity and supporting jobs; opening new markets for U.S. goods and services; and fostering innovation and investments in research and development."*

Apparently, information protection is said to have many merits. The most common argument for it is that the ability to exclusively enjoy the benefits of one's knowledge provides strong incentives to invest in effort to discover the information in the first place. Without such rewards, no one will be motivated to innovate. In addition, information acquisition often requires large capital outlay and will not be possible without attractive financial compensation.

The goal of this paper is to empirically assess the impact of restricted information transfer on innovation. However, there are a few empirical challenges in this paper. The amount of knowledge transfer among firms is difficult to measure. It is almost impossible to know exactly when information is transferred. Even if we know every such occurrence, each piece of information is unique and putting a value on it is simply infeasible. Moreover, even if the amount of knowledge transfer is measurable, it can be endogenous. Companies that have better access to rival information might be very different from those do not in

[1] https://www.whitehouse.gov/sites/whitehouse.gov/files/omb/IPEC/2016jointstrategicplan.pdf

multiple dimensions. The ability to innovate can also affect a firm's willingness to share knowledge; those which are less efficient at innovating might be more eager to acquire more outside information. Therefore, I use the staggered adoption of the Uniform Trade Secrets Act(UTSA) as a plausibly exogenous source of variation in knowledge sharing in this paper. The UTSA is a state-level legislation that strengthens protection of trade secrets. I discuss the details of this statute and provide the legal background on trade secret protection in Section 1.3.

I find that industry-level innovation declines as knowledge sharing becomes more restricted when more firms in the industry are protected by the UTSA. I argue that this decrease in Research and Development (R&D) efficiency is due to fragmentation of knowledge that inhibits recombination of ideas, hampers development of new technology that relies on others' work, and causes wasteful duplicative investments. The effect is economically significant as the average firm produces 6.6 fewer patents in an industry where all firms are protected as compared to one where none are. This is equivalent to a $176 million loss in value in 2017 dollar to each average firm [2]

To pin down the source of this decline, I look at firm-level innovation and find that the protected companies' innovation output is not affected and the decrease comes from the competitors of the protected firms. I present evidence that the decline is more severe for high-tech industries and companies seek alternative avenues to acquire information when the UTSA has been passed. These two pieces of evidence are consistent with the hypothesis that restricted knowledge transfer hurts innovation. I also explore other possible channels and conclude that they are at least not the primary force contributing to the lower industry-level innovation output. I show that higher performance of protected firms might explain why companies might push for higher protection of intellectual property.

Even though limiting information flow can lead to lower industry-level innovation, individ-

[2] The average value of a patent as calculated from the change in market equity when a patent gets approved according to Kogan et al. (2017) is $10.36 millions in 1982 dollar or $26.7 millions in 2017 dollar.

ual firms might prefer to be protected. If they are protected, they can obtain strategic information from their competitors while keeping their own knowledge to themselves. This can give them a competitive edge. When all companies are protected, no one can gain any advantage from being protected. However, the aggregate innovation level declines as a result. Even if firms are aware that they can potentially gain from others' information, the situation where everyone is protected might still be the preferred outcome. Companies know exactly the value of their own knowledge to themselves and can estimate relatively accurately how valuable it will be to their rivals. However, a firm might not have an accurate idea on type of knowledge its rivals have and how useful that would be to itself. This information asymmetry might contribute to firms' reluctance to share knowledge.

One issue with knowledge protection is that formal sharing agreements are not capable of replacing informal and accidental reveals because of a Catch-22 situation. Knowledge owners often will not disclose without contractual agreement on compensation while knowledge seekers are reluctant to enter into such agreements when they do not know what the paid information entails. This should be a point that the policymakers keep in mind when enacting trade secrets legislations.

I organize this paper as follows. I review related literature in Section 1.2 before providing a detailed account on trade secret laws in Section 1.3. Empirical framework is outlined in Section 1.4. I then present the main result in this study and offer an explanation for it in Section 1.5. Alternative mechanisms are discussed in Section 1.6. I discuss the internal validity of my empirical design and run some robustness tests in Section 1.8. I summarize and conclude in Section 1.9.

1.2. Related Literature

This paper will add a piece of empirical evidence to the long-time debate on the effects of trade secrets laws in the legal literature. Legal scholars have examined the cost and benefits in legal, social, and moral aspects (such as Bone (1998); Claeys (2011, 2012); Friedman et al.

(1991); Landes and Posner (2003); Lemley (2008); Risch (2007, 2011)). Proponents argue that such laws complement other intellectual property laws and encourage innovation and disclosure. In addition, it is unjust for one to reap the benefits of others' labor without paying for it. Opponents cautions against waste of social resources when an arms race between the protectors and invaders occur or duplicative investment is made (Bone, 2014).

This paper is related to the literature on the effects of intellectual property protection. Some theory papers outright assume that protection is positively correlated with R&D output e.g. Gilbert and Shapiro (1990) while some authors are more cautious about the relation e.g. Scotchmer and Green (1990). The empirical papers on this subject mainly focus on patent protection and find mixed results. Lerner (2009) could not establish a link between the strength of patent protection and innovation and attribute this, what he calls, puzzling result to possible measurement errors, time frames of the study, and the fact that the impact of such legal environment on innovation might simply be less that the literature has assumed. Using both interviews and econometric methods, Sakakibara and Branstetter (2001) also find no effect of patent law on innovation in Japan. A similar conclusion was drawn by Qian (2007) for the pharmaceutical industry. Moser (2005) suggests that patent laws could affect the direction of innovation. Specifically, poor patent protection would steer innovation into areas where patents are less important while better protection could help with the development of a more diverse innovation scene. Branstetter et al. (2006) observe increased technology transfer to affiliates when intellectual property rights improved. Scotchmer (1991) argues broad patent protection could discourage later-generation innovations because of the exclusivity awarded to the early inventors.

The two papers that are most closely related to this study are Png (2017) and Contigiani et al. (2017). Png (2017) finds that the UTSA is associated with higher R&D investment in larger and high-tech companies. He posits a direct and an indirect effect of the UTSA on R&D: the direct effect would be an increase in R&D; the indirect effect will be positive if own and spillover R&D are substitutes and negative if they are complements. He suggests that the indirect effect is either positive or negative but outweighed by the indirect effect. My results indicate that the latter scenario might be more likely. Contigiani et al. (2017) find that inventor-level patenting activities are adversely affected by trade secrets rulings that favor employers and curtail employee mobility. They argue that this observation is consistent with the explanation that restricted mobility discourages workers to signal quality to potential future employers. They argue that hindered knowledge recombination is unlikely to account for the decline since they do not see a decrease in the combinatorial novelty measure when labor becomes less mobile. This discrepancy in our findings could be due to the different types of trade secret legal changes we use and our distinctive interpretations of what recombination of ideas encompasses. Contigiani et al. (2017) utilize the Inevitable Disclosure Doctrine (IDD) which specifically limits the transfer of knowledge through labor movement while I use the UTSA which is a broader legislation that applies to a wider range of information exchange channels that include knowledge transfer between business partners, through consultants, and contractors etc. It is possible that restricted mobility can hurt innovation through the incentive and signaling channel as discussed in Contigiani et al. (2017) but reduced knowledge transfer in other forms can also lead to a decline in R&D output. While Contigiani et al. (2017) show that recombination of ideas is unlikely the main mechanism in their setup, I argue in this paper that knowledge transfer is important to innovation because of three different ways[3] in which innovation can be affected. I do not attempt to analyze each suggested possibility individually or disentangle one from another in this paper.

1.3. Legal Background

I describe both the broad legal environment of trade secrets protection and the UTSA specifically in this section. I also explain why the UTSA could potentially be used to analyze the effect of knowledge transfer on innovation.

[3]Knowledge recombination, building on previous work, and duplicate effort

1.3.1. Trade Secrets Laws

Before former President Barack Obama signed the Defend Trade Secrets Act (DTSA) into law on May 11, 2016, trade secrets, unlike other forms of intellectual property such as copyrights and patents, were largely governed at the state level (summarized in Figure 1). Before the introduction of the Uniform Trade Secrets Act (UTSA), courts relied on common law, which is the body of law derived from predecessors' rulings on similar cases, when deciding on trades secrets disputes. The modern common law on trade secrets draws its principles primarily from section 757 of the First Restatement of Torts (Pooley, 1985). However, section 757 had significant limitations. Being derived from cases prior to 1939, it is extremely outdated given the technological and industrial development since then. Also, it lacked a clear definition of trade secrets and were often interpreted in parts (Wong, 1987). Moreover, the Restatement is not a legally binding authority and the courts could decide whether to adopt it or not (Gettings, 2007).

The UTSA was published by the Uniform Law Commission (ULC) in 1979 and amended in 1985 to provide a legal framework to better protect trade secrets for US companies. Six states first adopted the act in 1981. By 2017, all 50 states and the District of Columbia have enacted the UTSA or similar statutes. Table 1 lists the year in which each state passes the UTSA.

The USTA strengthened trade secrets protection in several aspects. First, it not only clearly laid out but also expanded the definition of trade secrets. Most notably, the UTSA no longer requires information to be in continuous use to be protected (Kantner et al., 2013). This means that negative information such as failed experiments, which was previously not protected under common law in most states, is considered trade secrets by the UTSA. Some information that was previously not consistently treated as a trade secret is explicitly listed as examples of trade secrets by some states. For example, Texas adds "financial data" and "list of actual or potential customers or suppliers" to types of trade secrets. Second, misappropriation of trade secrets becomes more inclusive. Unlike most common law, the

UTSA does not require the use or disclosure of a trade secret; mere acquisition suffices (Png, 2017). Third, the UTSA enhances remedies available to the plaintiff. An injunctive relief is possible to eliminate any advantage gained from misappropriation. Punitive damages can be up to twice the actual damages. In addition, the "UTSA also contains a powerful fee-shifting provision that authorizes courts to award attorney fees where (i) a claim of misappropriation is made in bad faith, (ii) a motion to terminate an injunction is made or resisted in bad faith, or (iii) willful and malicious misappropriation exists" (Bombard, 2016). This potentially increases the litigation risk for misappropriators because the trade secret owner can be enticed by lawyers who charge contingent fees into filing a lawsuit she would otherwise has little interest in pursuing. Last, the UTSA brought about a greater sense of consistency and certainty. Previously, "a trade secret litigant have no reliable way to measure when liability will be imposed" (Wong, 1987).

The broader and clearer definition of trade secrets, harsher penalty, and higher certainty made available by the UTSA can deter perpetrators because they are now less likely to get away with trade secrets misappropriation and face direr consequences if convicted.

1.3.2. The UTSA and Knowledge Transfer

Before I explain how the UTSA affects information exchange among firms, I want to first touch upon the concepts of jurisdiction and choice of law.

When litigating a case, the plaintiff needs to make two important decisions: where to sue and which laws to invoke. A court needs to have both subject matter jurisdiction[4] and personal jurisdiction to hear a case. When the parties involved are citizens of the same state, the case should be litigated in a state court of that state. The plaintiff can elect to file a suit in a federal court if the parties have diverse citizenships and the amount in controversy exceeds $75,000. A corporation can be a citizen of both its state of incorporation and the state of its principal business location simultaneously. A dispute over properties can be litigated in the state where the properties are located. However, in the case of intellectual property, the

[4] For instance, federal courts have exclusive jurisdiction over cases on patent infringement and federal tax.

location is often more difficult to determine. Once the appropriate court is chosen, the court has to decide which laws to apply. Selecting laws is rather straightforward if the dispute involves a contract that contains "express choice of law" clauses. If not, state courts are more likely to choose the laws of their own jurisdiction on the grounds of familiarity unless under special circumstances. Some federal courts "short-circuit the process [of choosing laws] - simply applying their host state's privilege law without undertaking or even mentioning a choice of law analysis" (Spahn, 2014). Some courts apply the choice-of-law rules of the forum state and carefully analyze its host state's principles[5].

The vast majority of trade secrets lawsuits are against former employees or business partners and collaborators[6]. Some examples of business partners and collaborators are investors, independent contractors, suppliers, parties to a joint venture, and outside counsel or consultants. Often a non-disclosure agreement(NDA) is signed by the parties involved. Such "confidentiality agreements usually contain a choice of law clause specifying that the law of the Disclosing Partys state controls"(Myers, 2015). For instance, an NDA written by the University of Texas at Austin includes the following clause - "[t]he Agreement will be governed by the laws of the State of Texas, without regard to choice of law principles"[7]. Lawyers of a company are familiar with the laws of the state of incorporation of the company, but may be ignorant of the laws of other state with the exception of the state of Delaware (Pacces, 2010). Therefore, the governing laws specified in an NDA are likely to be that of the state of incorporation of the disclosing party.

While trade secret lawsuits can potentially be filed even if an NDA does not exist. In this study, I focus on the most common scenario where it is available and assume that the trade secrets of a company becomes more protected when the state of the company adopts the UTSA. Since the UTSA increases the litigation risk faced, a firm might be more hesitant

[5] Swortwood v. Tenedora de Empresas, S.A. de C.V., Case No. 13cv362-BTM (BLM), 2014 U.S. Dist. LEXIS 29247, at *28 (S.D. Cal. Mar. 6, 2014)

[6] citeAlmeling2010 put the number at 93% based on 358 state court cases and 394 federal cases on trade secrets with decisions issued between 1950 and 2008

[7] Document found on https://research.utexas.edu/wp-content/uploads/sites/6/2015/10/NDA_v6_1.doc

when hiring someone from a competitor for his or her knowledge. Consultants, bankers and external legal counsel must be more careful not to inadvertently facilitate the transfer of information when they provide assistance to a large number of firms. Project collaborators need to be more cautious if they want to use information they have access to in the joint program for other purposes.

1.4. Empirical Framework

The main empirical challenge in this research is the endogeneity of knowledge transfer. Companies with more information flow probably differ on other unobservable dimensions. Moreover, it is difficult to accurately measure the amount of information transfer. Therefore, I exploit the passage of the UTSA as a source of plausibly exogenous variation.

1.4.1. Industry-level Analysis

I have explained in the previous section that the UTSA protects the trade secrets of companies of the state. In other words, it is likely to decrease the information outflow from the protected companies. If restricted knowledge transfer hurts innovation, industry-level technological progress should decline when more companies in an industry become protected by the UTSA because the information of a firm is likely to be most useful to those in the same area. To investigate how information transfer affects the innovation output of an industry, I estimate

$$IndustryInnovation_{jt} = \beta_1 Protection_{jt-1} + \beta_2 Protection_{jt-2} + \lambda_j + \gamma_t + u_{jt} \qquad (1.1)$$

where $Innovation_{jt}$ is a measure of innovation output for industry j in year t; $Protection_{jt}$ is a market capitalization-weighted or equally weighted variable of level of trade secrets protection within the industry; λ_j is industry fixed effects. γ_t is year fixed effects. Lagged measures of $Protection$ are used to reflect that it takes some time for the effect of knowledge transfer to appear.

I derive industry-level measures of innovation and protection by calculating the equally weighted and market capitalization-weighted averages of the firm-level equivalents. Specifically, I define

$$Protection_{jt} = \frac{\sum_{i=1}^{N_j} w_{ijt} \times UTSA_{ijt}}{\sum_{i=1}^{N_j} w_{ijt}} \tag{1.2}$$

$UTSA_{ijt}$ equals one if firm i in industry j has passed the UTSA at time t. N_j is the total number of firms in industry j as defined by the 4-digit SIC codes. w_{ijt} is equal to 1 in the equally weighted case and the total market equity of firm i in industry j at time t if the weights are market capitalizations. Essentially, $Protection_{jt}$ is the weighted fraction of companies that are protected by the UTSA in industry j at time t. All firms in an industry are protected and information exchange is very limited if $Protection_{jt} = 1$; no firm is protected if $Protection_{jt} = 0$.

Similarly, industry-level measures of innovation are calculated from respective firm-level measures as follows

$$IndustryInnovation_{jt} = \frac{\sum_{i=1}^{N_j} w_{ijt} \times FirmInnovation_{ijt}}{\sum_{i=1}^{N_j} w_{ijt}} \tag{1.3}$$

It is difficult to measure the level of innovation. Therefore, I use three different measures to capture the innovative activities of firms more accurately. The first is the raw number of patents filed by a firm in a year that would ultimately be granted later on. The raw number of patents can give us a general sense of how productive a firm is in R&D. However, it does not take into account the quality of the innovation. The number of citations of a patent can be a proxy for importance and influence of a discovery. Therefore, I also include the forward citation-weighted number of patents to measure innovation. In addition, I use a stock market reaction-weighted measure developed by Kogan et al. (2017). It is constructed based on how much the market reacted when a patent is approved. This can reflect the internal value of a patent to the firm's shareholder.

1.4.2. Firm-level Competitor Analysis

The UTSA protects information of firms in that state from flowing to their competitors. Hence, it is the rivals of the protected that are most affected if knowledge transfer matters for innovation. Companies tend to benefit most from knowledge of their competitors. When more of a firm's competitors are protected, it might find it more difficult to move forward with its projects. To measure how well a firm's competitors are protected, I first identify the closest product rivals of a firm using a text-based measure introduced by Hoberg and Phillips (2010). Hoberg and Phillips (2010) assigns a similarity score to each pair of companies using information machine-read from their SEC forms. I define pairs with scores in the top 10% of the Hoberg and Phillips (2010) dataset as close rivals. Alternative measures such as top 15% and 20% are used in the robustness tests. The level of trade secret protection enjoyed by firm i's competitor(s) at time t is defined as

$$CompetitorProtect_{ijt} = \sum_{k \in \mathbf{K}_{it}} score_{ikt} \times UTSA_{kjst} \tag{1.4}$$

$UTSA_{kjst}$ measures whether firm i's rival k in state s has passed the UTSA by year t. $score_{ikt}$ represents the similarity between firm i and its rival k in year t. The higher the score the more similar firms i and k are. A score of 1 means both firms produce exactly the same thing where as a score of 0 reflects that the product space of these companies does not overlap at all. $\mathbf{K}_{ijt}$ is the subset of companies that are firm i's rivals in year t.

I regress various innovation and performance measures on a variable representing the level of trade secrets protection the close rivals of a company have to show this effect or

$$y_{ijst} = \beta CompetitorProctect_{ijt-1} + f_i + \lambda_{jt} + u_{it} \tag{1.5}$$

f_i is firm fixed effects and λ_{jt} is industry-year fixed effects. Standard errors are clustered at state level.

1.4.3. Firm-level DiD Regression

For some purposes in this study, I also employ the commonly used difference-in-differences methodology. Specifically, to show the impact of restricted knowledge outflow on protected firms, I estimate

$$y_{ijst} = \beta UTSA_{st} + f_i + \lambda_{jt} + u_{it} \tag{1.6}$$

where y_{ijst} is the outcome of interest for firm i in year t; $UTSA$ is an indicator that is equal to 1 if the state has enacted a UTSA statute by year t; f_i is firm fixed effects; λ_{jt} is industry-year fixed effects. Standard errors are clustered at state level.

1.4.4. Data and Summary Statistics

I describe my data sources and present summary statistics in this subsection. Firm financials are from Compustat and stock data are from CRSP. Merger and acquisition data and strategic alliance data are downloaded from SDC Platinum. Adoption of UTSA before 1998 is from Png (2017) and passages after 1998 are compiled through news searches and state government documents. Patent data are from Professors Noah Stoffman's website [8]. Product rival data is downloaded from Professor Gerard Hoberg and Gordon Phillips's website [9].

Descriptive statistics are provided in Table 17. Panel A shows that innovation is very right screwed with a few number of firms investing extremely heavily in R&D and producing most of the patents. Stock volatility in Panel B is the daily stock return volatility averaged over a year. As we can see in Panel C, in about half of M&A the target and the acquiror are from the same industry as defined by their 3-digit SIC codes. Technology transfer happens in about 13.5% of strategic alliances on average.

[8]https://iu.app.box.com/v/patents
[9]http://hobergphillips.usc.edu/idata

1.5. Results and Analysis

In this section, I first show that industry-level innovation decreases as more and more firms in an industry become protected by the UTSA (Subsection 1.5.1). Then, I present some additional evidence that is consistent with the hypothesis that restricted knowledge transfer hurts innovation(Subsection 1.5.2). Last, I test some alternative mechanisms and show that they are unlikely to by the primary force driving the industry-level decline (Subsection 1.6).

1.5.1. Industry-Level Innovation

Using the specification outlined in Subsection 1.4.1, I regress innovation measures on the lagged industry-level trade secret protection variable that I constructed. I find that overall innovation output declines as more firms in an industry becomes protected.

The results using equal weights and weighted by market capitalization are presented Tables 4 and 3 respectively. The independent variable, which is between 0 and 1, can be interpreted as the weighted portion of companies protected by trade secret laws in an industry. When it becomes harder for firms doing similar businesses to learn from one another, they are less efficient in innovating. When market capitalization-weighted variables are used, companies in an industry with no firms protected by the UTSA file 10 more patents next year (or 18 more on a citation-adjusted basis) than if all firms in the same industry are protected by the UTSA (Table 3). If equally weighted measures are used, firms in that industry still produce 3 more patents (or 5 more on a citation-adjusted basis) in the former case than the latter one (Table 4). Table 5 presents the results using citation-weighted number of patents with variables weighted by market capitalization when up to four lags are used. However, although all estimates are negative lags of trade secret protection beyond 2 years are not statistically significant.

One interesting result is that the number of patents weighted by stock market reaction upon patent approval is not affected by trade secret protection. The interpretation of this result is that restricted flow of knowledge hurts firms R&D efficiency - the rate at which it can successfully innovate. However, the value of each successful patent application to the firm's shareholder is unaffected by trade secret laws. This could be due to the fact that firms select R&D projects based on their strategic needs in advance. Therefore, once the project is completed and relevant patents are granted, it is not straightforward to see why the value of the project would be affected by how well the firm and its competitors are protected by trade secret laws. However, stronger trade secret legislation can impact how fast a company or an industry can innovate. Often, companies in the same industry can be researching on similar projects. For instance, a firm is trying to find out from 10 different methods which one works. It has tried Methods 1 to 4 know that they fail and its rival has tried Methods 5 to 8 and know these are not the right ones either. If somehow these two companies can share their information, they would be able to succeed much sooner on average. When more firms are protected by trade secret legislations, it takes longer for them to develop new technologies. Hence, the patent output of the industries declines.

1.5.2. Knowledge Sharing and Innovation

I show in the previous subsection that innovation is hurt at the industry level when trade secrets are better protected. In this subsection, I will provide further evidence that the decrease in information flow is the likely cause that drives down the patent output by showing that (1) industry-level decline in R&D output is more severe for high-tech industries; (2) decreased innovation at the industry level comes from the competitors of those being protected; (3) companies seek alternative avenues to acquire information when the UTSA makes it more difficult to do so.

High-tech industries are most affected

R&D tends to be more intensive and complicated in high-tech industries. Therefore, we would expect to see sharper decline in innovation output in the high-tech industries if restricted knowledge transfer is the underlying mechanism of the industry-level decrease that I have showed previously. When a discovery is more complex and involves more steps, knowing others' experiments, failed or successful, or having access to others' technology that could serve as a foundation to what one has in hand becomes more crucial.

To test for the aforementioned hypothesis, I run a regression that is similar to the previous industry-level analysis but with interactions between the high-tech industry dummy and the *Protection* variable added to capture the difference in impact between the low- and high-tech industries.

$$\begin{aligned} IndustryInnovation_{jt} =& \beta_1 Protection_{jt-1} + \beta_{12} Protection_{jt-1} \times HiTech \\ &+ \beta_2 Protection_{jt-2} + \beta_{22} Protection_{jt-2} \times HiTech + \lambda_j + \gamma_t + u_{jt} \end{aligned}$$

The citation-weighted number of patents in a low-tech industry in which all firms are protected by the UTSA is 7.7 lower in a year than that in the same industry if no firm is protected. However, for a high-tech industry the number is 45 (Table 6). On caveat when interpreting the results is that the comparison is based on a complete shift i.e. a change from none to all. One should expect the impact to be proportionally smaller if only one state passes the UTSA in that year. Also, the average number of patents is higher for the high-tech industries to begin with. The results using equal weights are similar although less significant (Table 7).

How restricted knowledge sharing affects rivals

We know that industry-level innovation decreases when more firms in that industry becomes protected by the UTSA. If reduced information exchange is the main driver behind this result, we should see that the rivals of the protected firms are mainly responsible for the decline at least for the period immediately afterward. This is because the decrease in knowledge transfer associated with the UTSA is likely to be directional. The protected firms enjoy less information outflow without suffering less inflow. Therefore, the rivals of the protected firms who would otherwise benefit from sharing of knowledge are likely to be the ones most affected. Although the protected firms seem unharmed in the immediate term, the long-run effect can also be negative for them. Withholding information from rivals might give the firm a temporary edge. However, without this piece of information, it might take the rivals of the firm longer to develop a technology that will later benefit the same firm that has withhold the crucial information.

I analyze the effect of trade secrets protection of a firm's rivals on the firm's innovation using the specification outlined in Subsection 1.4.2. I identify the rivals of a firm using the text-based similarity score provided on Professor Gerard Hoberg and Gordon Phillips's website [10]. The score is calculated for pairs at a level that is as granular as the 3-digit SIC code. I define close competitors as those with scores in the top 10 percent. Alternative definitions yield qualitatively similar results. I then created a variable that measures how well a firm's close rivals' trade secrets are protected as defined in Subsection 1.4.2. Table 8 presents the regression results of innovation and performance measures on this rival protection variable. If one average close rival[11] becomes protected by the UTSA, the number of patents produced by the firm decreases by approximately 4. This effect is even more pronounced (8 lower) if we use forward citation-weighted number of patents.

How firms react

When companies cannot simply acquire competitors' knowledge by hiring an employee of the rival who knows or extract that information from a contractor or consultant, they have to resort to other potentially more costly methods of obtaining useful information. When a firm knows that a competitor has valuable information, it might be willing to enter a formal agreement to access that by paying a fee on it. I find that the likelihood of a firm being a party in strategic alliance with technology transfer increase by 3 percentage point more after the adoption of the UTSA for companies protected by it. The unconditional mean of technology transfer involved in a strategic alliance is 13.5% (Table 9). The acquiror and the target are 13.8 percentage points more likely to be from the same-industry if the

[10] http://hobergphillips.usc.edu/idata

[11] On average, the similarity score between close rivals as defined in this paper is 0.15.

target is protected by the UTSA than if it is not after the passage of the UTSA (Table 9). Being in the same industry is defined as the main SIC code of the target matches any of the acquiror's SIC codes. The same exercise was also performed at the 3-digit SIC code level and produces very similar results. However, this conclusion can only be drawn for public targets. Column 3 of Table 9 repeats the analysis for the entire space of M&As and the result no longer holds. This might be due to the higher transparency of public firms. If the main goal behind an acquisition is to acquire valuable knowledge, then it will only make sense if the acquiror is certain that the target does possess the information that is seeking since the cost of executing an M&A is very high. Public companies regularly disclose information in various filings that can help potential acquirors better identify targets and also assess the value that can be generated if the M&A goes through.

This observation highlights the problem that parties might not be willing to enter into a costly knowledge exchange agreement without knowing exactly what type of information it will acquire. However, the knowledge owner might be reluctant reveal without being guaranteed that it will be compensated for. This is probably why that despite an increase in formal information exchange through technology transfer in strategic alliances, the R&D output still decreases.

1.6. Alternative Mechanisms

While the decline in industry-level R&D output and the three additional pieces of evidence I show in Subsection 1.5.2 are consistent with the hypothesis that restricted knowledge transfer hurts innovation. There are some other mechanisms that could possible explain the industry-level decrease as well. I explore two such alternative channels in this section.

1.6.1. Substitution from Patenting to "Padlocking"

Companies have the option to either patent an innovation or protect it in secrecy ("padlocking"). A patent gives the innovators the exclusive right to use the invention for a number of years. The downside is that in order to file for a patent, the inventor has to ultimately publish the details on the invention and anyone can use the patented technology after the patent expires. If a company chooses to keep an invention as a secret, it can potentially profit from it with no competition as long as (1) it can keep it a secret; (2) others do not reverse engineer the product; (3) others do not independently develop it. Some companies have been able to benefit from trade secrets for extensive periods of time. For example, the Coca-Cola recipe has been kept a secret for over 100 years. However, the obvious threat of "padlock" is that any of the aforementioned conditions do not hold.

A number of factors can affect how they make the decision to patent or "padlock". It might not make much sense to protect an innovation through secrecy if the product or process can be easily reverse engineered. For instance, the inventor of Rubik's cube has a higher chance of making a good profit if he patents it since any competitor can easily replicate the product by disassembling one of the original Rubik's cube. Besides the nature of the innovation, operational and organizational factors are also important to companies when deciding whether to patent or padlock. If only a handful of people need to know the secret for large-scale production to run smoothly, then it is much easier to keep the invention a secret that when an entire factory is inevitably exposed the secret in the manufacturing process. The strength of trade secret legal protection can affect how companies choose as well. When firms know that there is a good chance they can recuperate their losses and earn compensation through litigation if their secrets are stolen, they may be more inclined to protect their technology as trade secrets.

The adoption of the UTSA strengthened trade secrets protection and might give companies more incentives to substitute from patenting to "padlocking". If substitution occurred, then a decrease in number of patents should be observed for the protected firms at the firm-level as well. I argue that substitution is not the dominant channel by showing that companies with increased trade secret protection do not experience a decrease in patents. Table 10 presents the regression results from a firm-level differences-in-difference analysis. The number of patents from firms with increased trade secrets protection from the UTSA only rises by 0.3 as compared to the mean of 27.57. This estimate is also not statistically significant with a t-statistic of 0.8. The empirical evidence suggests that legal protection on trade secrets plays an insignificant role in influencing firms' patenting decisions; firms are perhaps more likely to choose whether to patent or "padlock" based on the nature of the innovation.

Contigiani et al. (2017) analyze the substitution between patenting and secrecy using a different method. They look at a subsample of patents that are "discrete". "Discrete" inventions are simpler and more difficult to protect using secrecy as compared to "complex" technology. They argue that substitution is unlikely to entirely account for the decrease in inventor-level innovation because the decline is also observed for the "discrete" subsample.

1.6.2. Monopolistic power thwarts innovation

If important innovative discoveries occur as random positive shocks to firms, those that are lucky to have technological breakthroughs might be able to achieve higher monopolistic power due to their superior technology. When the market becomes less competitive, those controlling the market might have less incentive to actively innovate while the smaller players might not have enough resources to develop new technologies. As a result, the innovation level of the industry can decrease.

I show in this subsection that this is not the main mechanism through which innovation level declines by presenting evidence that the industries do not become more concentrated when more firms in the same industries are protected by trade secret laws. Table 11 presents the regression results of the level of industry concentration as indicated by Herfindahl-Herchman Index on industry trade secret protection. The effect of information flow on industry is not economically nor statistically significant. Therefore, it is unlikely that innovation decreases as a result of higher monopolistic power.

1.7. The Benefits of Trade Secret Protection

Is there any benefit of trade secret protection? I show in the previous sections that innovation suffers both at the industry level and for rivals of the protected. Can trade secret protection bring some benefits at least to the ones being protected? If a firm's information becomes harder to access for outsiders but its own access to other's knowledge remains unchanged. This could potentially make the protected firm more efficient at R&D than its competitors if the information concerned are research-related. However, as I show in Section 1.6.1, the protected firm will not be more efficient at R&D than if it were not protected. The relative advantage is likely to come from its competitors being less efficient.

If a protected firm is privy to its rivals' pricing and marketing strategies but not vice versa, it could enjoy an increase in performance as it knows how to price and market its product to edge out its competition. The same could happen when its rivals become less efficient in product development. In Table 12, firms whose trade secrets are protected enjoy a 13% higher increase in EBITDA and a 10% higher increase in sales than firms that are not protected. Investors might like trade secret protection for their portfolio companies because it offers more certainty that any fruit from R&D investment will not be shared with competition. The last column in Table 12 shows that the average daily stock volatility of the firms protected decreases by 0.13 percentage point more than those not protected.

The advantage gained from being protected by the UTSA could be one of the reasons why many firms and industry leaders have advocated the adoption of the law. When some firms are enjoying the protection offered by the UTSA, those that are not protected have reasons to push for the same protection as well so that they will not be at a competitive disadvantage. Arkansas, Idaho, Louisiana, Minnesota, and North Carolina first passed the law in 1981. Now all US states have passed the statute with the last two states, Massachusetts and New York, adopting it in 2017. The relative advantage is likely to disappear when all players enjoy the same level of protection. However, the aggregate innovation could decline as a result.

1.8. Internal Validity and Robustness

1.8.1. Confounding Factors

One important assumption of this study is that the adoption of the UTSA by various states is somewhat exogenous. Png (2017) documents that the there is no special force pushing for or fighting against the adoption UTSA. His conclusion after interviewing legal experts is that the passage of the UTSA was rather random in a number of states. He also runs several tests to show that a number of firm characteristics cannot predict the adoption of the UTSA. However, the circumstances surrounding the passage of a law are admittedly complicated. Hence, I control for a number of observable variables that could potentially confound the result. Amore et al. (2013) find that deregulation across US states druing the 1980s and 1990s has beneficial effects on the quality and quantity of innovation activities. If the implementation of these banking deregulations is correlated with the passage of the UTSA, we might have incorrect estimates although it should theoretically bias against the result in this paper. Restriction of labor mobility can potentially hurt innovation as well (Samila and Sorensen, 2011). Therefore, I also add the "Non-compete Enforceability Index" constructed by Garmaise (2011) to my original specifications. Controls are 1-year lags of the independent variables of interest to avoid the problem of "bad controls" when contemporaneous controls are used because the adoption of the UTSA could potentially affect banking regulations and enforcement on non-competes [12]. Tables 13 and 14 present the industry-level regressions of innovation variables on level of trade secrets protection level in industries using market equity-weighted and equally weighted measures respectively. The results are similar to when controls are not included.

1.8.2. Test for Pre-existing Trends

The main result of this paper is at industry level not firm or state level. If there is lobbying influence, it is extremely unlikely that the lobbyists can ensure that every state that hosts

[12] Regressions using controls contemporaneous to the independent variable of interest were also performed and produce similar results.

any firms of an industry passes the UTSA almost simultaneously. The argument that the UTSA was passed because innovation was declining does not hold either since the an industry often consists of firms from different states and a state usually has companies in a number of industries. Nevertheless, I test for pre-trends in the data using the specification below

$$y_{ijst} = \sum_k \beta_k (UTSA_{is} \times k\ years\ post\ UTSA) + f_i + \lambda_{jt} + u_{ijst} \tag{1.7}$$

The coefficient estimate β_l for year k captures the difference in the dependent variable for the treated and control groups in year k. *k years post UTSA* is a dummy variable that is 1 if the observation is for Year k post the adoption of the UTSA. Firm fixed effects f_i and industry-year fixed effects λ_{jt} are included as before. The coefficient estimates are graphed with their 95% confidence band in Figure 2. Prior to the UTSA, the differences in innovation (Subplots 2.3(a) and 2.3(b)), risk (Subplots 2.3(c) and 2.3(d)), performance (Subplots 2.3(e) and 2.3(f)), and size (Subplots 2.3(g) and 2.3(h)) between the treated and control groups are virtually zero.

1.8.3. Level of Analysis

I present the main result of this paper at industry level: innovation is lower when more firms in an industry become protected by the UTSA. To identify the source of the decline, I perform two firm-level analyses: I first look at how firms are affected when it becomes more difficult to obtain information from their competitors; and I also test for the effect of the UTSA on innovation of the protected firms. The regressions are run at the firm level when I analyze the benefits firms protected by the UTSA might enjoy.

The main result of this study is at industry level because I want to emphasize the potential social cost of such protective legislation. My hypothesized explanation for this industry-level decline is a drop in information exchange that occurs through labor movement, collaboration projects, contractor jobs, and consulting relationships etc. Therefore, I further my analysis at firm level. It would be interesting to see if similar patterns exist at the inventor level but this is beyond the scope of this study and Contigiani et al. (2017) provides a good analysis at the inventor level using a different type of change in legal environment.

1.8.4. Other Robustness Checks

To show that the decline in industry-level innovation is not driven by a single or a handful of industries, I run the same industry-level analysis excluding industries with most observations one by one. The coefficient estimates are presented in Table 15. I find similar results.

Multiple definitions of high-tech industries and "same-industry M&A" and different time horizons before and after the adoption of the UTSA to ensure robustness of the results. The differences-in-difference regression results presented in this paper are done using a "stacked" method (see Gormley and Matsa (2016)), but a "cohort" (see Bertrand and Mullainathan (2003)) method was also tested and yield similar results.

1.9. Conclusion

I investigate the impact of knowledge sharing on innovation using the staggered adoption of the UTSA as a plausibly exogenous source of variation in inter-firm information flow in this paper. I find that innovation becomes less efficient when information is more fragmented, duplicative work happens, and companies cannot build on others' experiences. This result is more pronounced for high-tech industries where knowledge sharing might be most important. I identify the source of this decrease in efficiency as companies that have less information inflow. To overcome the problem of limited informal knowledge exchange, companies are more likely to acquire technology in strategic alliances or through merger and acquisitions. These are imperfect solutions as knowledge owners do not want to disclose guaranteed compensation and the knowledge seeker do not want to guarantee without knowing what information it is getting. Therefore, the amount of voluntary knowledge transfer in the form of formal agreements might be much less that what is socially optimal. I argue that the decrease in innovation is unlikely to be a result of substitution from patenting to "padlocking" by showing that when information flow is more restricted in a state, the innovation level of companies in that state is not affected; but that of the competitors of firms in that state declines. I also rule out that the effect is coming from higher monopolistic power by showing that market concentration is not affected by the UTSA.

Trade secret protection might provide a competitive edge to the protected. Such benefits are likely to disappear when all market participants enjoy such protection. However, the lower level of knowledge transfer can hurt the innovative efficiency of society as a whole. While seeking to improve the competitiveness of the firms they represent, policymakers might also want to keep the potential social cost of such legislations in mind.

CHAPTER 2 : Profit and Loss Sharing in the IPO Market

2.1. Introduction

When companies first float their shares in initial public offerings (IPOs), they tend to use firm-commitment underwriting, which by its terms imparts asymmetric incentives. The underwriter builds a book of investors and then sets the offer price, and if the market price proves to be higher, the investors get the entire resulting profit, and the underwriter gets just its fee per share. If the market price is instead lower, the underwriter is still obliged to buy the shares for the offer price minus the fee, so is in principle on the hook for the entire resulting loss. So the offer price is effectively the strike price on a put the underwriter is short, and it is well understood that, everything else equal, this encourages lower pricing.

It is also well understood that industry practices can soften the edges of this contract. When investors learn that the market value is below the offer price, and they see the lead underwriter trying to support the market price at the offer price, they can put the loss back to the underwriter by selling into the price support, or they can bear some of it themselves by holding. And when investors earn big profits on hot IPOs, they can give some back through other interactions, such as brokerage commissions, with the underwriter. The goal of this paper is to incorporate such sharing into a model of firm-commitment underwriting, thereby allowing us to see how it affects the choice of underwriting fees and offer prices, and also to estimate the magnitudes of profit and loss sharing in practice.

The analysis starts with the firm-commitment contract, and models two sequential optimizations: the issuer's choice of underwriting fee, i.e. gross spread, and the underwriter's choice of offering price. We take three objects as exogenous to the analysis: the underwriter's subjective distribution over potential market values per share, the share γ of profits above the offer price that accrue to the underwriter, and the share β of losses below the offer price that accrue to the underwriter. Thus, firm commitment without sharing corresponds to $\gamma = 0$ and $\beta = 1$, and sharing is captured by higher γ and lower β. We solve for the equilibrium first for a general distribution of the market value, and then to extract more results, we assume a particular functional form, i.e. the lognormal distribution, where the key exogenous parameter is its uncertainty parameter σ.

We find profit and loss sharing to have very different effects on equilibrium fee and price setting. An increase in profit sharing has little or no effect on the offer price; the result is instead an increase in the underwriting fee. So the underwriter benefits both from the higher share and the higher fee, whereas the issuer simply loses from the higher fee. But when the investors share more of the underwriter's losses, both the offer price and the fee increase, with a net positive effect for both the issuer and the underwriter.

With respect to uncertainty, we find not surprisingly that it generally (thought not in extreme cases) lowers the offer price, and we also find that it increases the fee. Higher uncertainty transfers wealth from issuer to underwriter.

What levels of loss and profit sharing prevail in the IPO market? To find out, we fit the model to the data. This fitting requires us to proxy for the underwriter's uncertainty about the market value; for this purpose we use the realized volatility of the market price in the months after the syndication period. Our principal finding is that investors share a large fraction of the underwriter's potential losses from overpriced IPOs, about half at the point estimate. However, we find no evidence of profit sharing.

This paper is organized as follows. Section 2.2 discusses related literature. Section 2.3 details the set-up of the model. Section 2.4 presents the analysis and discusses results. Empirical evidence is presented in Section 2.5. Section 2.6 summarizes and concludes. Proofs are in the Appendix.

2.2. Related Literature

The underpricing of IPOs was documented empirically by Stoll and Curley (1970), Reilly (1973), and Ibbotson (1975), and analyzed theoretically by multiple subsequent studies.

Many of these focus on asymmetric information. The issuer is assumed to be more informed than the investors in Allen and Faulhaber (1989), Welch (1989), and Chemmanur (1993), and this is seen to motivate high-quality issuers to signal their types by discounting to combat the resulting "lemons" problem of Akerlof (1970), i.e. that only low types are willing to sell. In Rock (1986) the asymmetric information behind underpricing is instead between investors, driving a winner's curse problem that can scare away less-informed potential investors. Similarly, Welch (1992) attributes underpricing to informational cascades in which an investor's perception of other investors' interests affect her action. In Benveniste and Spindt (1989), Benveniste and Wilhelm (1990), and Spatt and Srivastava (1991), the underwriter can learn about the market value from the investor community during bookbuilding, and this encourages under-reaction in price revisions to investor enthusiasm. In Baron (1982), the underwriter is more informed that the issuer and underpricing arises from the subsequent agency problem. Along the same agency-problem lines is Habib and Ljungqvist (2001), which argues that underpricing substitutes for market effort. Some other theories do not rely on asymmetric information and posit that underpricing is due to underwriter's fear for legal liabilities (Tiniç, 1988; Patricia J. Hughes, 1992), or the underwriter's pursuit for higher profits from market-making in the aftermarket (Boehmer and Fishe (2001)). They will in turn be rewarded with more allocations in the future. Empirically, Cornelli and Goldreich (2001) finds that regular investors receive favorable allocations especially when the IPO is heavily oversubscibed. Hanley and Hoberg (2010) document that underpricing is less severe when the prospectus of the IPO is more informative. Aggarwal et al. (2002) find that underpricing is more positively correlated with institutional allocation. Ljungqvist and Wilhelm (2003) argue that a more fragmented ownership structure can partly explain underpricing.

Several empirical studies address the significance and intensity of the underwriter's aftermarket price support. The underwriter has an affirmative obligation to support the price of sagging offerings, and towards this end can buy back the entire Green Shoe, almost always 15% of the offering, to soak up excess supply, and then can keep buying after that

((Hanley et al., 1993; Benveniste et al., 1996)). The extent of the underwriters' obligation is unclear. They do not buy every share flipped back to the market, but as Ellis et al. (2000) document, they do buy a lot. And buying these shares is not necessarily costly, but it is if their expected returns are poor, and both Hanley et al. (1993) and Miller and Reilly (1987) show that the future returns of struggling offerings are indeed poor. So it follows that, as Chemmanur et al. (2010) argues, investors share losses with underwriters when they hang onto, rather than sell, the shares whose prices the underwriters are trying to support.

For a more complete and detailed review on the literature on IPO, there are surveys by Ritter and Welch (2002), Ljungqvist (2007), and Ritter (2011).

2.3. The Model

The model is as follows. A risk-neutral issuer chooses the fee $k > 0$ that it will pay a risk-neutral underwriter to float a fixed number of shares (the precise number of shares is not important; it's important only that the number of shares is fixed). The flotation is through a firm commitment contract, which means that

- The underwriter chooses the price at which shares will be offered to the public
- The underwriter buys the shares from the issuer for $(1 - k)$ times the offer price
- The underwriter then allocates the shares to bidders for the offer price, unless the true value of the shares is less than the offer price, in which case the underwriter sells the share for their true value.

To allow for the possibility that the underwriter is affected only partially by any shortfall of the true value from the offer price, due to the willingness of investors to bear some of this loss themselves, we let β represent the portion of the shortfall affecting the underwriter, i.e. the loss share. So if for example the offer price is 10 and the true value is 8, then the underwriter experiences a loss per share of 2 if $\beta = 1$, and a loss per share of only 1.2 if $\beta = 0.6$. Perhaps the easiest way to think of β is that initially, investors buy the whole offering at the offering price. And then, if and when it becomes apparent that the true value of a share is below the offer price, and the underwriter engages in price support, investors can either hold on to the shares, to bear some or all of the loss as the market price descends to the true value, or potentially buy shares from the underwriter at the currently inflated market price, again to bear some or all of the loss to the true value, or they can sell the shares to the underwriter engaging in price support, so that the underwriter bears that loss. So if and when the true value is below the offer price, $1 - \beta$ captures the fraction of the difference borne by all investors other than the underwriter.

Similarly, to allow for the possibility that the underwriter gains some benefit from profits earned by the investors to whom it allocates shares, such as from those investors routing future business to the underwriter, we let γ represent the portion of any excess of the true value over the offer price affecting the underwriter, i.e. the profit share. So if the offer price is 10 and the true value is 12, then if $\gamma = 0.02$ the underwriter enjoys a gain per share of 0.04. With this notation, the incentives imparted simply by the firm commitment contract are captured by setting $\beta = 1$ and $\gamma = 0$.

The true value p is unknown when the underwriter prices the shares. The cumulative density function (CDF) of the distribution of the true value at the time of pricing is $F(p)$, which is continuous and differentiable, and is known to both the issuer and the underwriter. For some purposes we specify that this distribution is log-normal with mean μ and standard deviation σ for the underlying normal distribution. In the log-normal case, the issuer needs to know only σ, not μ. The underwriter takes the fee as given and chooses the price p^* that maximizes its expected revenues. The issuer chooses the fee k^* that maximizes its revenue, given the effect of this choice on the underwriters subsequent choice.

We refer to F as the distribution of the true value, not of the market price, to avoid confusion from the possibility that the market price differs from the true value due to the underwriter's price support. There are other reasons why the market price might depart from some notion of 'true value', e.g. irrational exuberance, but F is not intended to reflect these other reasons.

The parameter β is intended to capture investors' willingness to bear losses when it turns out that the offer price exceeds the true value. This willingness is presumably not unconditional. In particular, investors are unlikely to be so willing to bear losses for the underwriter if the underwriter prices the offering above the expected true value in the first place. Thus, we assume that $\beta < 1$ applies only when a good faith attempt to underprice the offering goes awry. So $\beta < 1$ applies only when the offer price is below the expectation; otherwise, $\beta = 1$.

The chronology of the model is as follows. First, the underwriter offers a fee k to the underwriter to float its shares through a firm-commitment contract. If the underwriter accepts, then the underwriter chooses the offer price p^*. By the terms of the firm commitment contract, the underwriter then buys the shares from the issuer for $(1-k)p^*$ per share and offers the shares to the public for p^*. If the true value $p > p*$ then the underwriter sells all shares for p^* each, and also receives a profit share of $\gamma(p - p^*)$ per share. If the true value $p < p^*$ then the underwriter suffers a fraction β of the loss $p - p^*$. That is, the underwriter receives p^* for each share in this case, but also suffers the loss $\beta(p - p^*)$.

There are two optimizations in the model. First, the issuer chooses the optimal fee, which is the fee that maximizes its revenue, given its effect on the underwriter's optimization, and then the underwriter chooses the optimal offer price, which is the offer price that maximizes its expected revenue, given the distribution of the true value.

2.3.1. The Model

We start with the underwriter's optimization, which adds profit and loss sharing to the objective function in Choie (2016). We then work back to the issuer's optimization. So for a given fee k, the underwriter maximizes

$$\underbrace{kp^*}_{\text{Revenue}} + \underbrace{\beta\left(\int_{-\infty}^{p^*} xf(x)dx - F(p^*)p^*\right)}_{\text{Expected losses from overpricing}} + \underbrace{\gamma\left(\int_{p^*}^{\infty} xf(x)dx - (1-F(p^*))p^*\right)}_{\text{Expected gains from underpricing}} \tag{2.1}$$

over p^* such that (2.1) is greater than 0. The price also needs to be low enough that the investor has a non-negative expected payoff

$$(1-\beta)\left(\int_{-\infty}^{p^*} xf(x)dx - F(p^*)p^*\right) + (1-\gamma)\left(\int_{p^*}^{\infty} xf(x)dx - (1-F(p^*))p^*\right) \geq 0 \quad (2.2)$$

So the underwriter gets the revenue per share from buying for $(1-k)p^*$ and selling for p^*, plus a share β of losses arising from overpricing and a share γ of investors' gains arising from underpricing. The investors, who are the buyers of the shares, bear the share of losses from overpricing that the underwriter is not responsible for and enjoy the profit from underpricing less the cut by the underwriter. Note that the investors do not play an active role in selecting the fee or the offer price in our model. The issuer solves

$$\max_{k\geq 0}(1-k)p^* \quad (2.3)$$

where k is the percent of offer price paid to the underwriter as fees. The issuer takes into consideration the price that the underwriter will choose given this fee when setting the fee. Also, the issuer will only decide to go public if she receives at least her exogenous reservation price which is $\underline{p}$ per share

$$(1-k)p* \geq \underline{p} \quad (2.4)$$

This condition is to capture the fact that the company has value to the issuer even if it remains private.

2.3.2. Relative Size of Loss Share, Profit Share, and Fee

Before analyzing each player's optimal choice, we want to digress slightly and examine the parameter range that makes most economic sense for our discussion in this subsection.

Differentiating the underwriter's objective function (2.1) with respect to p^* we get

$$k + \beta(p^* f(p^*) - F(p^*) - p^* f(p^*)) + \gamma(-p^* f(p^*) - (1 - F(p^*)) + p^* f(p^*)) \tag{2.5}$$

Simplifying (2.5) yields

$$k - \gamma - (\beta - \gamma)F(p^*) \tag{2.6}$$

The second derivative of the underwriter's expected profit with respect to p^* is simply .

$$-(\beta - \gamma)f(p^*) \tag{2.7}$$

Let us first look at the case where the underwriter shares more profit than loss i.e. $\gamma > \beta$. We define $\bar{p}$ to be the offer price such that the investor breaks even

$$(1-\beta)\left(\int_{-\infty}^{\bar{p}} xf(x)dx - F(\bar{p})\bar{p}\right) + (1-\gamma)\left(\int_{\bar{p}}^{\infty} xf(x)dx - (1 - F(\bar{p}))\bar{p}\right) = 0 \tag{2.8}$$

Notice that $\bar{p} = \mathbb{E}(p)$ when $\beta = \gamma$. Hence, $\bar{p} < \mathbb{E}(p)$ when $\gamma > \beta$. We will only consider the case where $\underline{p} < \bar{p}$ since otherwise there would not exist an IPO. Note that the underwriter's payoff will always be positive when $p^* < \mathbb{E}(p)$ if $\gamma > \beta$, so the underwriter's participation constraint never binds in this case.

If the issuer sets the fee k such that $\gamma > k > \beta$, the underwriter's payoff is U-shaped with respect to p^*; it decreases with p^* when $p^* < F^{-1}\left(\frac{\gamma-k}{\gamma-\beta}\right)$ and increases with p^* when $p^* > F^{-1}\left(\frac{\gamma-k}{\gamma-\beta}\right)$. Therefore, the only sensible options for the underwriter are the highest price that gives the investors an expected payoff of zero, $p_H^* \equiv \bar{p}$, and the lowest price that the issuer is willing to accept, $p_L^* \equiv \frac{\underline{p}}{1-k_L}$. We show in Appendix A.1 that the issuer sets the fee just high enough for the underwriter to choose p_H^* instead of p_L^*. Therefore, there is no reason for the issuer to select a k that is greater than γ since he can achieve the highest price possible by paying a fee that is less than γ (Expression (A.5) is always less that γ).

When $\beta > \gamma$, can k be less than γ? If so, (2.6) is negative, meaning that the underwriter will pick the lowest possible offer price which is clearly suboptimal for the issuer. Similarly, if k is greater than β, (2.6) is positive.[1], which means that the underwriter will choose the highest possible offer price. Therefore, for the rest of this paper we will focus on the case where loss share is greater than the fee, and the fee is greater than profit share ($\beta > k > \gamma$) since it is this range that makes economic sense.

2.3.3. Model Solution

When $\beta > k > \gamma$, we can derive the expression of the price from (2.6)

$$F(p^*) = \frac{k-\gamma}{\beta-\gamma} \tag{2.9}$$

Given this relation between fee k and offer price p^*, what fee would the issuer choose to pay to underwriter? The issuer maximizes

$$(1-k)p^* \tag{2.10}$$

over the fee, k. Knowing that the underwriter will price according to (2.9), the issuer thus maximizes

$$(1-k)F^{-1}\left(\frac{k-\gamma}{\beta-\gamma}\right) \tag{2.11}$$

Differentiating (2.11) with respect to k yields

$$(1-k)\frac{dF^{-1}}{dk}\left(\frac{k-\gamma}{\beta-\gamma}\right) - F^{-1}\left(\frac{k-\gamma}{\beta-\gamma}\right) \tag{2.12}$$

[1](2.6) can be re-arranged into $(k-\beta) + (\beta-\gamma)(1-F(p^*))$.

Applying the formula for the derivative of an inverse function, we get

$$F^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)F'\left(F^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)=\frac{1-k^*}{\beta-\gamma} \tag{2.13}$$

which means that k^* is the k that solves this equation, and that p^* is the offer price that k^* implies.

2.4. Analysis

From these equations we get several predictions about IPO fees and offer prices:

Result 1: The offer price is $F^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)$, where k^* is the fee, β is the loss share, γ is the profit share and F is the cdf of the true value.

Result 2: The probability of overpricing is $\frac{k^*-\gamma}{\beta-\gamma}$, where k^* is the fee, β is the loss share, γ is the profit share and F is the cdf of the true value.

To extract the other dynamics this result implies, we must grapple with the endogeneity of the fee to the other parameters. Fortunately, there is one simple but powerful result we can extract with little effort. Suppose $\beta = 1$, i.e. the underwriter absorbs all losses from underpricing. Then in equilibrium, an increase in the profit share increases the fee but does not affect the equilibrium offer price. To see this, suppose the profit share increases from γ_0 to $\gamma_0 + \Delta$, and that the equilibrium fee implied by γ_0 is k_0^*. If the fee is increased to $k_0^* + \Delta\frac{1-k_0^*}{1-\gamma_0}$ then

$$\frac{1-k_0^*-\Delta\frac{1-k_0^*}{1-\gamma_0}}{1-\gamma_0-\Delta}=\frac{1-k_0^*}{1-\gamma_0} \tag{2.14}$$

and

$$\frac{k_0^*+\Delta\frac{1-k_0^*}{1-\gamma_0}-\gamma_0-\Delta}{1-\gamma_0-\Delta}=\frac{(k_0^*-\gamma_0)(1-\gamma_0-\Delta)}{1-\gamma_0)(1-\gamma_0-\Delta)}=\frac{k_0^*-\gamma_0}{1-\gamma_0} \tag{2.15}$$

which mean that both the left-hand and right-hand side of the equation are unchanged, so the equality still holds. And since this is true for any value of γ_0 including $\gamma_0 = 0$, we have a result that holds for any differentiable distribution which we can state as follows:

Proposition 1. *If the underwriter bears all losses from overpricing, and if the fee is k_0^* when the profit share is 0, then an increase of the profit share to $\gamma > 0$ increases the fee by $\gamma(1 - k_0^*)$ but leaves the offer price unchanged.*

It is worth pausing to consider what Proposition 1 means. It means that if we start with the standard firm-commitment contract, whereby the underwriter bears all the losses if the offer price is too high, and then we let the underwriter share the investors' profits from underpricing, there is ultimately no effect on the offer price, and thus no effect on underpricing. The effect is actually on the fee, as the issuer finds it optimal to offset the effect of the profit share by sharing more of the offer price. This also means that the underwriter benefits twice from the profit share: besides the profit share itself, it also gets more fee from the issuer to combat the increased incentive to price lower.

The implications of the loss share, as opposed to the profit share, are not immediately apparent from the equation. However, we can explore the dynamics by assuming a particular distribution for p.

Assume that the distribution of the true value is log-normal with mean μ_p and standard deviation σ_p. The mean and standard deviation of the underlying normal distribution are denoted by μ and σ respectively[2]. Then the equation that k^* solves, i.e. the issuer's FOC, can be written as

$$\left(\frac{1-k^*}{\beta-\gamma}\frac{\sigma}{\phi(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right))} - 1\right) exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) + \mu\right) = 0 \tag{2.16}$$

[2]By definition of log-normal distribution, $\mu = log(\mu_p) - \frac{\sigma^2}{2}$ and $\sigma = \left(log\left(1+\left(\frac{\sigma_p}{\mu_p}\right)^2\right)\right)^{\frac{1}{2}}$

Or more simply

$$\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)=\left(\frac{1-k^*}{\beta-\gamma}\right)\sigma \tag{2.17}$$

where Φ and ϕ are the CDF and PDF, respectively, of the standard normal distribution. Because σ figures in this equation but μ does not, this tells us that the issuer needs to know σ but not μ when setting the fee, and thus does not need to know everything the underwriter knows about the market price, only the precision with which the underwriter knows whatever it knows. We can also rewrite (2.9) as

$$p^* = exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\mu\right) \tag{2.18}$$

to obtain an expression for the offer price.

With this distributional assumption, we find that (1) IPOs will be underpriced; (2) more uncertainty leads to lower pricing and higher fees; (3) the underwriter gains while the issuer loses from higher uncertainty; and (4) more loss sharing by the underwriter results in lower fee but more severe underpricing.

2.4.1. Underpricing

An IPO is said to be underpriced if the offer price is below the expected market price. In the parameterization of our model, this corresponds to the following definition:

Definition 1. *An IPO is underpriced if the offer price determined by the underwriter is lower than the expected true value:*

$$p^* = F^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) < \mathbb{E}[p]$$

We can show that underpricing always obtains, provided the underwriter's precision clears the hurdle set by the following assumption.

Assumption 1. *The standard deviation σ of the normal distribution underlying the log-*

normal distribution from which the true value is drawn satisfies the upper bound

$$\sigma < \sqrt{\frac{2}{\pi}} \left(\frac{\beta - \gamma}{2 - \beta - \gamma} \right) \equiv \bar{\sigma}$$

This can be stated equivalently in terms of the parameters of the log-normal distribution:

$$\frac{\sigma_p}{\mu_p} < \sqrt{exp\left(\frac{2}{\pi} \left(\frac{\beta - \gamma}{2 - \beta - \gamma} \right)^2 \right) - 1}$$

where μ_p and σ_p are the mean and standard deviation of the distribution of the true value.

That this is a low hurdle in the base case where $\beta = 1$ and $\gamma = 0$ is easily apparent. With these parameters, the maximum amount of uncertainty $\bar{\sigma} = \sqrt{\frac{2}{\pi}}$ or $\frac{\sigma_p}{\mu_p} < \sqrt{exp\left(\frac{2}{\pi}\right) - 1} \approx$ 0.943. Therefore, in this case, Assumption 1 limits the standard deviation of uncertainty about the true value to slightly less than the expectation, so the precision it rules out is quite low. To see how this bound on precision varies as we move from the base case, Figure 5 plots the upper bound on σ (top plot) and on σ/μ (bottom plot) it implies for different combinations of β and γ. These upper bounds are little affected by γ, but they fall more quickly with β. So this assumption requires the underwriter to be more certain of the true value when it bears less downside risk.

In the parameter space defined by this assumption, we always see underpricing.

Proposition 2. *The IPO will always be underpriced.*

Proof. See Appendix A.2. □

The underwriting contract sets up an asymmetry: by raising the offer price a dollar, the underwriter gains the fee on that dollar if the true value turns out to be higher, but loses β dollar if the true value turns out to be lower. The issuer is free to combat this asymmetry with a higher fee but the fee the issuer chooses results in underpricing.

2.4.2. *Uncertainty*

As the underpricing dynamic is driven by uncertainty over the true value, it is intuitive that underpricing increases with uncertainty, which is what we find. Consistent with the previous proposition, this is also subject to an upper bound on uncertainty:

Proposition 3. *Underpricing increases as uncertainty, σ, rises when σ is low or moderate*[3].

Proof. See Appendix A.3. □

This is unsurprising from the option-pricing perspective: underpricing lowers the strike price on the option the underwriter is short, so the temptation to underprice more is stronger when the volatility is higher. Underpricing also increases the odds of sharing profits if $\gamma > 0$. This increase in underpricing from greater uncertainty occurs even though the issuer combats the effect through higher fees:

Lemma 1. *The fee or gross spread, k, increases as uncertainty, σ, rises.*

Proof. See Appendix A.2. □

When uncertainty is very high, a further increase in volatility affects the likelihood of overpricing less than when uncertainty is lower. This is true if the distribution of true price has higher probabilities centered around the mean like in a normal or lognormal distribution. Therefore, combined with the fact that a higher fee is set by the issuer when uncertainty increases, underpricing decreases with uncertainty when *sigma* is high.

The combination of lower pricing and higher fees implies directly that the issuer is worse off:

Lemma 2. *The issuer's payoff decreases as uncertainty, σ, rises.*

Higher uncertainty gives the underwriter a higher fee, though on a lower price. The net

[3]When $\beta = 1$ and $\gamma = 0$, the ratio between the standard deviation of price and the mean of price, $\frac{\sigma_p}{\mu_p}$ needs to be lower than 0.519.

effect, we find, is positive:

Lemma 3. *The underwriter's payoff grows as uncertainty, σ, rises.*

Proof. See Appendix A.4 $\square$

So the underwriter always underprices, and prices lower as uncertainty grows. Uncertainty makes the underwriter better off on net, given the adaptive response of the issuer, and also makes investors better off, since they are the ones paying the lower price. The issuer is the big loser. The issuer would presumably combat this effect by seeking out an underwriter with high precision, which it has the opportunity to do at the bake-off when underwriters compete for the mandate.

2.4.3. Loss Share and Profit Share

We saw with general distributions that, when the underwriter bears all losses, the profit share raises the fee without affecting the offer price when the underwriter bears all losses. In this section we use the log-normal distribution to explore the effect of profit and loss shares more generally. We start by observing that the fee decreases as β rises, or to put it another way, the issuer pays a higher fee when the investors bear more of the losses:

Proposition 4. *The fee or gross spread, k^*, decreases as the underwriter's loss share, β, rises.*

Proof. See Appendix A.5 $\square$

At the same time, the underwriter lowers the offer price as β rises, which is to say, more loss sharing by investors leads to higher offer prices:

Proposition 5. *The offer price, p^*, decreases as loss share, β, rises.*

Proof. See Appendix A.6 $\square$

For the underwriter, the net effect of bearing more losses and getting a lower fee on a lower price is negative:

Proposition 6. *The payoff to the underwriter decreases as the loss share, β, rises.*

Proof. See Appendix A.11 $\square$

And for the issuer, the net effect of paying a lower fee on a lower price is negative:

Proposition 7. *The payoff to the issuer decreases as the loss share, β, rises.*

Proof. See Appendix A.8 $\square$

To summarize, when investors share more of the underwriter's losses, fees and offer prices increase, with a positive net effect for both the underwriter and the issuer. For investors, the combination of sharing more losses and paying higher prices is plainly negative. This analysis takes the loss sharing as exogenous and thus does not explain why investors voluntarily do it, and in a one-shot game it makes little sense that they would. However, the literature documents that helping investors in one IPO improves access to the next, and this could provide the explanation. Also, this analysis does not explore the relation between information production by the underwriter and loss share, and committing to supporting prices in the market could encourage information production and reduce uncertainty (Prabhala and Puri, 1999).

Regarding the underwriter's share of profits, the positive effect on the fee found above for $\beta = 1$ holds in general with the log-normal distribution.

Proposition 8. *The fee or gross spread, k^*, increases as profit share, γ, rises.*

Proof. See Appendix A.9 $\square$

The difference from the $\beta = 1$ case is now the profit share increases the offer price.

Proposition 9. *The offer price, p^*, increases as profit share, γ, rises.*

Proof. See Appendix A.10 $\square$

The underwriter gets a higher fee, charges a higher price and gets a higher profit share, so it stands to reason that it benefits when the profit share increases:

Proposition 10. *The payoff to the underwriter increases as profit share, γ, rises.*

Proof. See Appendix A.7 □

The net effect for the issuer is negative:

Proposition 11. *The payoff to the issuer decreases as profit share, γ, rises.*

Proof. See Appendix A.8 □

Table 16 summarizes the comparative statics results in this and the previous sections. For illustration of the magnitudes of these effects, we take the mean and standard deviation of the distribution of the market price to be 20 and 2, respectively, and plot the comparative statics of the other parameters.

The top graph in Figure 3 plots the effect of loss and profit shares on the equilibrium fee, and the bottom graph shows their effect on the equilibrium offer price. The fee increases as the profit share grows, while the positive effect on the offer price is barely perceptible. The loss share significantly affects both fees and pricing. As β declines from 1, indicating increasingly more loss absorbed by investors, both the fee and the price increase, and this is true whether the profit share is zero or ten percent.

Figure 4 addresses all three parameters, β, γ and σ, at once. The columns of graphs represent increasing values of γ, left to right, and the rows represent increasing values of β, top to bottom. Within each graph we see the effect of increasing σ on the fee (blue line) and the offer price (red line). Each graph shows the fee rising with uncertainty; the main change across the graphs is the u-shape of the offer price with respect to uncertainty when the loss share is sufficiently low.

2.5. Empirical Evidence

In this section, we test our model predictions and provide some empirical evidence of price support. We discuss our data source and the summary statistics before presenting empirical evidence on our model predictions.

2.5.1. Data and Summary Statistics

The data used in this study come primarily from three sources. 13036 IPOs between January 1st, 1980 and December 31st, 2014 come from the Thomson Financial Securities Data Corporation (SDC) new issues database. 4904 IPOs with offer price less than \$5, unit offers, natural resource limited partnerships, banks and S&Ls, SPACs, REIT, closed-end funds, and ADRs are excluded from our sample. We extract stock price and shares outstanding data from CRSP for our IPO sample. And data on institutional holdings of new issues come from the Thomson Reuters 13F Institutional Holdings database.

Table 2.6 reports descriptive statistics of IPOs by period. The gross spread decreases slightly but stays near 7% throughout the sample. Underpricing is highest during the 1999-2000 dot-com era, and lowest during the 2008-09 financial crisis. The size of the average IPO increases tenfold from \$25.44 Million in the 1980s to \$261.5 Million after 2009. The daily volatility between 1 and 4 months post-IPO is generally around 3-4%, except for the dot-com era when it rises to 7.27%.

2.5.2. Model Predictions

Our model predicts that IPOs will be underpriced, and it is well understood that the data bear this out. In our sample, 74.1% of IPOs are underpriced and the average underpricing (measured, as usual, to the first-day close) is 17.7%.

Our model also predicts that fees and underpricing grow when uncertainty about the true value grows. These predictions are testable with a proxy for the underwriters' uncertainty, and for this we use the ex-post realized volatility of the stocks on the secondary market.

From this perspective, the finding in Ritter (1984) that, among the IPOs of 1980, underpricing increases with ex-post volatility bears out the prediction about underpricing. We run a similar test on our own sample, relating both underpricing and fees to the daily volatilities from above. This is summarized in Figure 7. IPOs are sorted into quintiles from the least volatile (Quintile 1) to the most (Quintile 5). The vertical axis represents the gross spread minus 7% in the left panel. We subtract 7% from the gross spread to make the trend more visible since fees congregate at this level. The plot shows that the fees grow as volatility increases. The bars in the right panel represent the percent underpricing, and as predicted, this also increases with the proxy for uncertainty. Figure 8 repeats the exercise in Figure 7 for different time periods. The trend is generally consistent across periods except for the financial crisis which saw few IPOs (Figure 9).

Since fee and price are determined jointly in our model, we restrict our sample to IPOs with gross spread equal to exactly 7% in order to gain more insight to the dynamic between uncertainty and price. A 1 percentage point increase in stock volatility in associated with a more than 4 percentage increase in 1st-day return of an IPO (Table 19). Size of IPO and the interaction between size and volatility are included in some specifications even though we do not take into account size in our model because size is likely to affect both volatility and underpricing.

2.5.3. Estimation of Loss Share and Profit Share

To gauge the incidence of profit and loss sharing at work in the IPO market, we estimate β and γ using the equations below

$$\mathbb{E}\left[FirstDayReturn_i - exp\left(\frac{\sigma_i^2}{2} - \sigma_i \Phi^{-1}\left(\frac{k_i^* - \gamma}{\beta - \gamma}\right)\right)\right] = 0 \tag{2.19}$$

$$\mathbb{E}\left[\mathbf{1}_{p_i^* > p_i^1} - \frac{k_i^* - \gamma}{\beta - \gamma}\right] = 0 \tag{2.20}$$

$$\phi\left(\Phi^{-1}\left(\frac{k_i^* - \gamma}{\beta - \gamma}\right)\right) = \left(\frac{1 - k_i^*}{\beta - \gamma}\right)\sigma_i \tag{2.21}$$

Expressions (2.19) and (2.20) are expectations that should hold on average. Expression (2.19) says that the expected first-day return in the data should be the underpricing predicted by the model.[4] Expression (2.20) makes use of the model-implied likelihood that an IPO turns out to be overpriced. Expression (2.21) is essentially the issuer's first-order condition which in principle holds for all IPOs individually. However, we do not force (2.21) on every IPO in the data but instead require this expression to be true on average in our estimation. Also, the post-market return volatility may be a better estimate of relative rather than absolute uncertainty that the underwriter is facing. In particular, the underwriter's uncertainty about the market value may be similar to volatility over some number of days, but that number does not have to be 1. Therefore, we add another parameter to estimate, m, which is a multiple on post-market return volatility that gives us the uncertainty level from the underwriter's perspective. We observe k^* directly, as it is the gross spread from the SDC data.

In total, we have 3 moment conditions and 3 parameters. We first estimate the unknown parameters β, γ, and the volatility multiple using generalized method of moments (GMM) with Newey-West covariance matrix. We performed the exercise first without restrictions on the parameters and then again with some constraints [5]. The estimation result is reported in Table 20.

The loss share is estimated at close to a half, meaning that investors share about equally with the underwriter in a cold IPO's losses. The profit share, on the other hand, is essentially zero, indicating that the investors' profits are not passed to the underwriter. The volatility multiple of about 3 or 4 implies that the amount of uncertainty the underwriter faces is

[4] Since underpricing is measured to the first-day close, and since the first-day close is potentially affected by price support, this is only approximate. The alternative is to use a price that post-dates price support, but this introduces other variation and so is also approximate.

[5] $0 < \beta < 1$, $0 < \gamma < 1$, and Volatility Multiple> 0.

equivalent to approximately two weeks of stock volatility.

Next, we conduct a simple exercise by essentially solving for β and γ using the issuer's first order condition (2.21) and $\mathbb{P}(p_i^* > p_i^1) = \frac{k^*-\gamma}{\beta-\gamma}$ for every single IPO in our data to obtain a sample of values of β and γ setting the volatility multiple to 4.14 or 3.10. Table 21 reports the mean and standard deviation of the calculated βs and γs. The calculated results are overall consistent with the estimates from GMM.

The low value of the profit sharing estimate could be attributed to the empirically observed fee which is approximately 7%. Despite the frequent allegations that the investment banks are charging too much for IPOs, 7% is still a rather small fraction of the amount raised. As we discussed previously (Table 16), a high fee is associated with a high profit share and a low loss share. it is therefore not surprising that our estimate of profit share is small and that of loss share is relatively large. If profit sharing is commonplace, we should expect to observe a higher fee empirically.

2.5.4. Evidence of Loss Sharing

In Chemmanur et al. (2010) we see that institutions which hold their IPO allocations for a longer period of time are rewarded with more allocations. In Hanley et al. (1993) we see that IPOs tend to be overpriced, i.e. have bad expected returns, in times when price support is likely. We expand on this finding by estimating, for each day in IPO event time, what the market-excess return is going forward a month for the IPOs trading below, near and above the offer price. Together with the Chemmanur et al. (2010) finding, this sheds light on the role of institutions in sharing losses by holding IPO shares when they would profitably be sold.

Figure 10 plots 1-Month (21 Trading Days) holding period returns for 3 groups of IPOs. The groups are determined by the following rules

Group 1: The offer price is more than \$1 below the Day-N price

Group 2: The offer price is within \$1 of the Day-N price

Group 3: The offer price is more than $1 above the Day-N price.

To be more specific, if it is Trading Day 11, we compare the closing price on Day 11 to the offer price of an IPO and place it into one of the 3 groups. Then we calculate the return we would have achieved if we were to hold it for a month until Trading Day 32. We do this for all IPOs in our sample and compute the average 1-month return for each group on each trading day. We repeat the exercise for Trading Days 1 - 100. The horizontal axis represent the trading day on which the closing price is used to determine the groups. Returns are adjusted by CRSP value-weighted market return assuming a market beta of 1, and the 95% confidence interval for the Group 3 returns is indicated with shading. The returns of the underpriced IPOs continue to be high and those of the overpriced IPOs continue to be low for an extended period of time, and the confidence interval for the overpriced IPOs is generally below 0 for the entire syndication period. We learn from this that on average one would incur a loss when holding an overpriced IPO during the syndication period. This represents at least some of the loss sharing driving β below 1.

2.6. Summary and Conclusion

We analyze the IPO market with a model that allows profit and loss sharing, as well as uncertainty over the value of the IPO shares, to affect the offering price and the underwriting fee. We start with the standard firm-commitment contract and introduce parameters capturing this uncertainty and the degree to which investors share the deal's losses with the underwriter and the underwriter shares the deal's profits with the investors. We derive a number of predictions, and we take the model to the data to gauge the incidence of such sharing in the market.

The main theoretical finding is that both varieties of sharing lead to higher underwriting fees and higher offer prices, but loss sharing has a much stronger effect on offer prices than does profit sharing. The net effect is that loss sharing benefits both the underwriter and the issuer, whereas profit sharing benefits the underwriter while hurting the issuer. We also find that uncertainty raises fees and generally lowers offer prices, while benefiting the underwriter and hurting the issuer.

We fit the model to a large sample of IPOs and find that, viewing the data through the lens of the model, loss sharing is substantial but profit sharing is not. At the point estimates, investors share half of the losses that the firm-commitment contract assigns to the underwriter, whereas the underwriter shares none of the profits accruing to the investors. We also find that the underwriter's uncertainty over the shares' value, at the time of pricing, amounts to about two weeks of the shares' aftermarket volatility.

Our analysis does not address the social-welfare implications of profit and loss sharing, but it does still shed some light. The effect of profit sharing is ultimately just to enrich underwriters. Not only do they get the profit share, they also get more fee. The small effect on the offer price means the investors simply lose the profit share and the issuer loses the extra fee, so the underwriter benefits at the expense of both other parties. By contrast, loss sharing benefits not only the underwriter but also the issuer at the expense of the investors. So loss sharing lowers the cost to the issuer of going public, which implies more companies going public and gaining the benefits that follow from that.

The natural follow-up to this study is to endogenize what we take as exogenous, i.e. the profit and loss shares, the uncertainty and the choice of contract. These are promising lines of research we leave to others.

Figure 1: Development of Trade Secrets Legislation in the USA

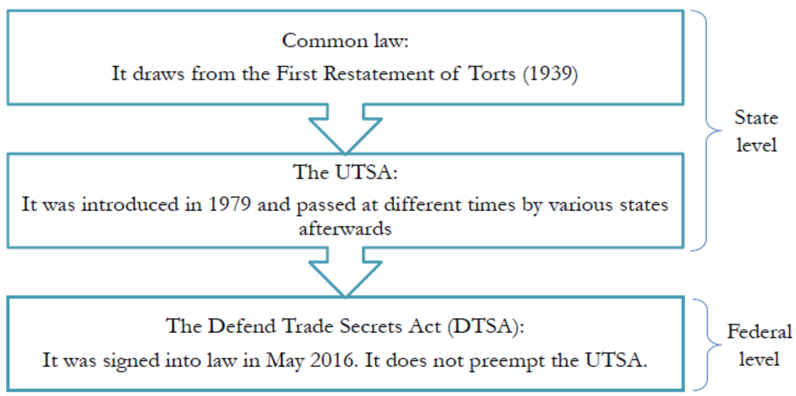
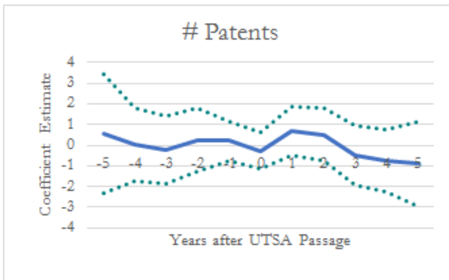


Figure 2: Pre-trends



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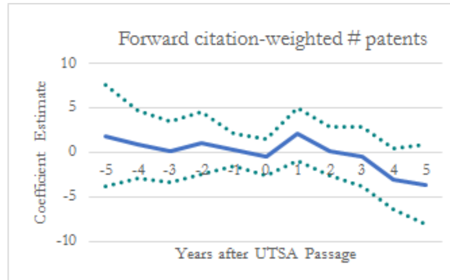

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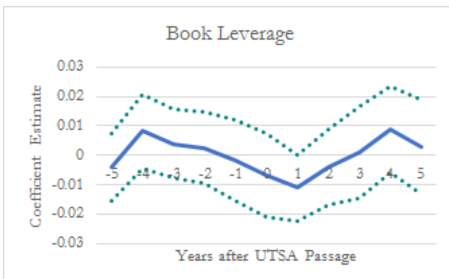

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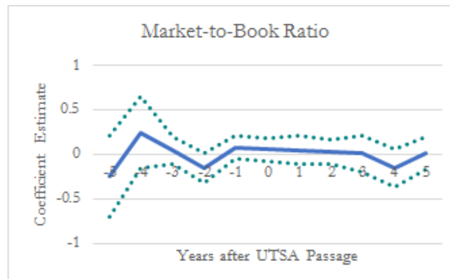

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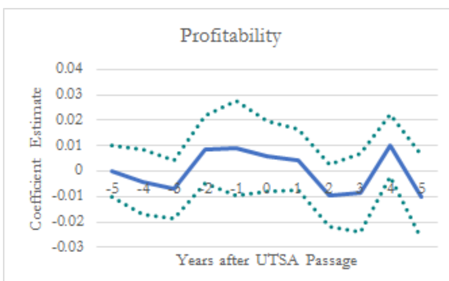

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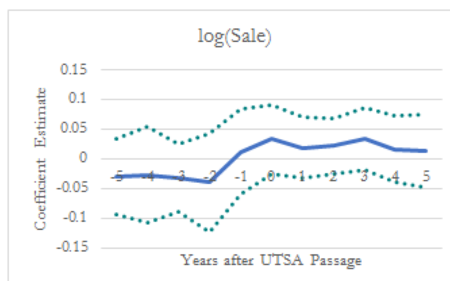

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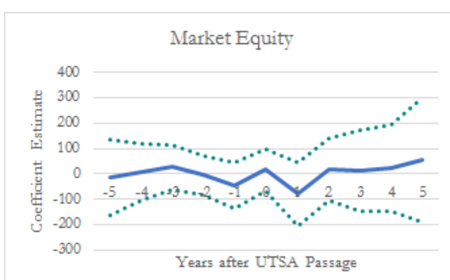
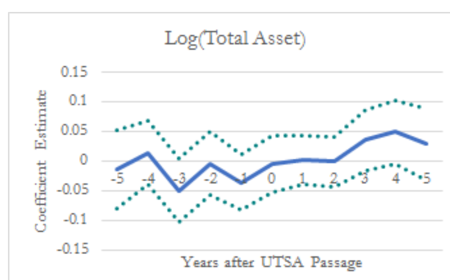
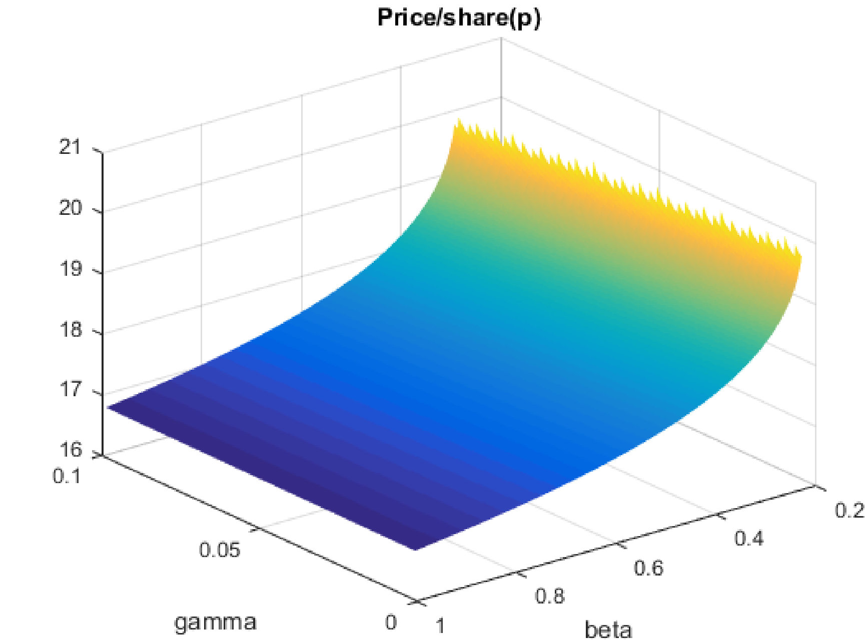


(g)

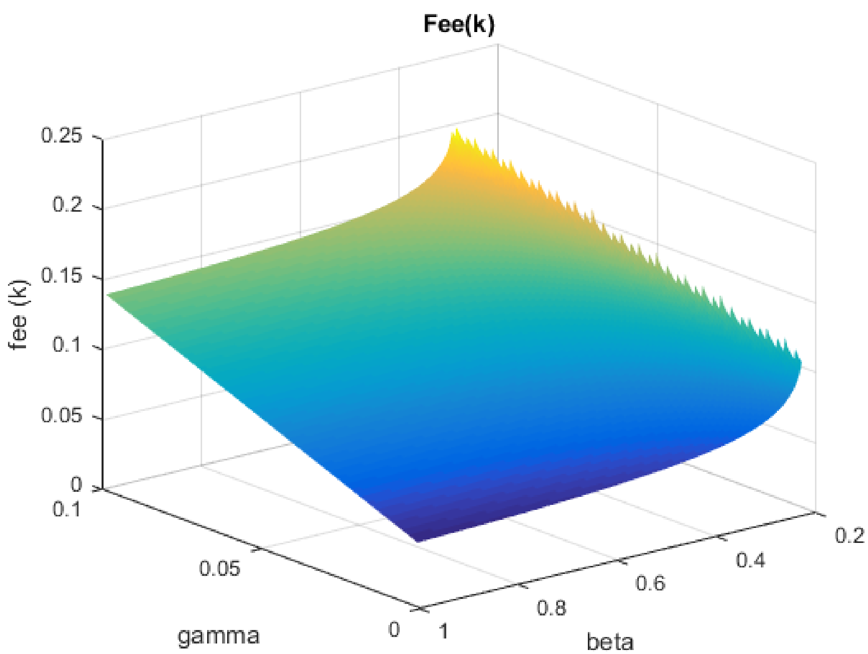


(h)

Figure 3: Offer price and Fee with respect to β and γ



(a)



(b)

Figure 4: Price and Fee with respect to Volatility for Different β, γ Combinations

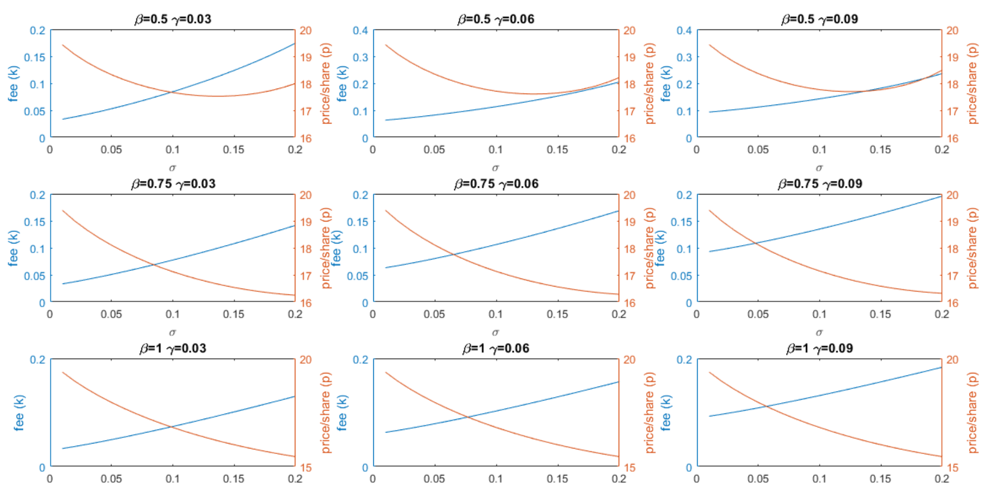
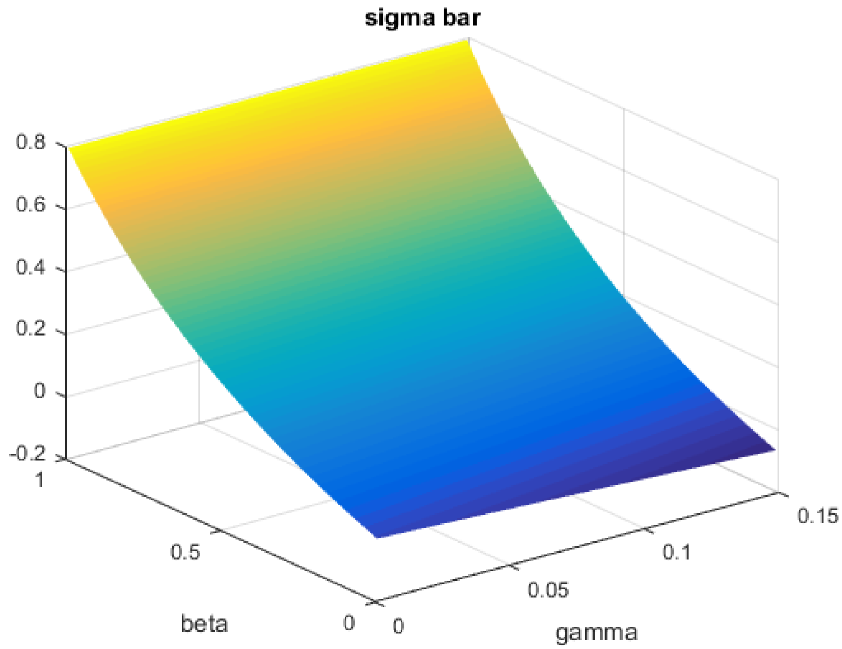
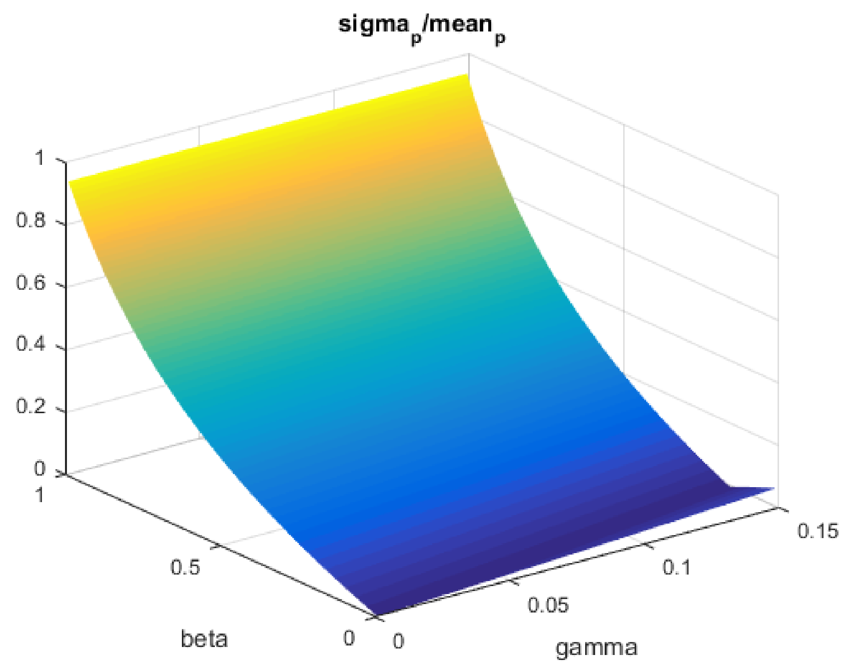


Figure 5: Visualization on Level of Restriction Assumption 1 Imposes.



(a)



(b)

Figure 6: Values of $\hat{\sigma_p}$ for Different Values of β When $\gamma = 0$, 0.05, and 0.10.

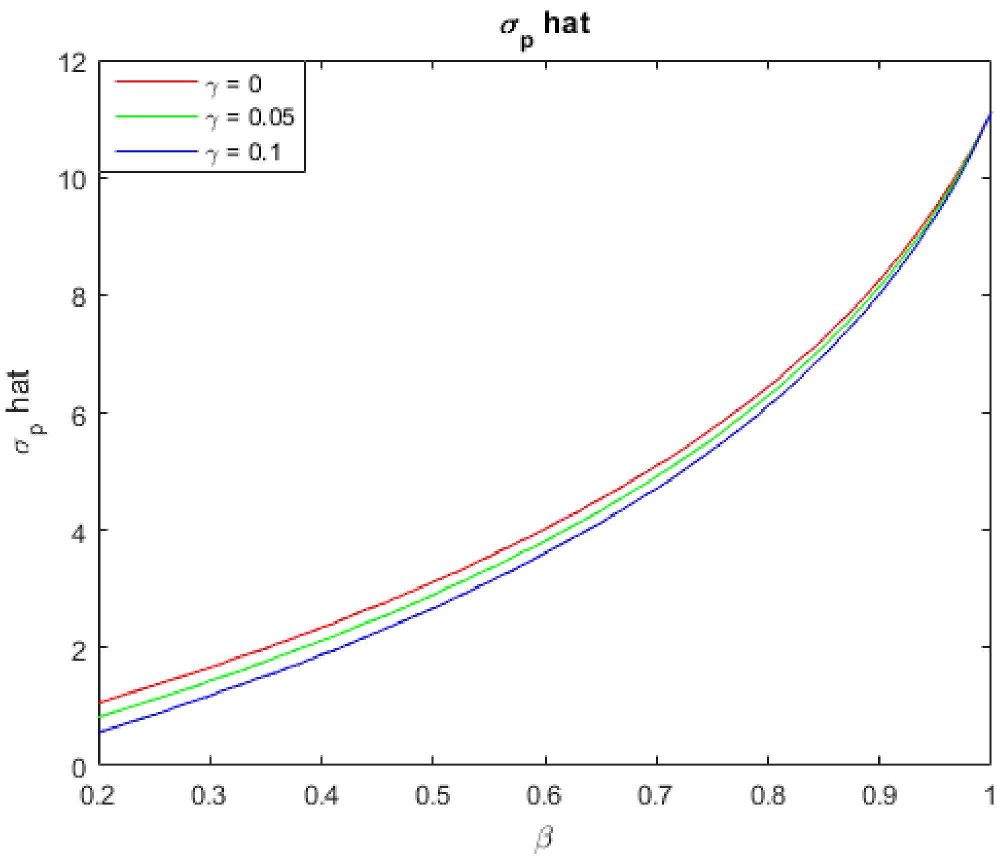


Figure 7: Spread and Underpricing by Volatilities Quintiles

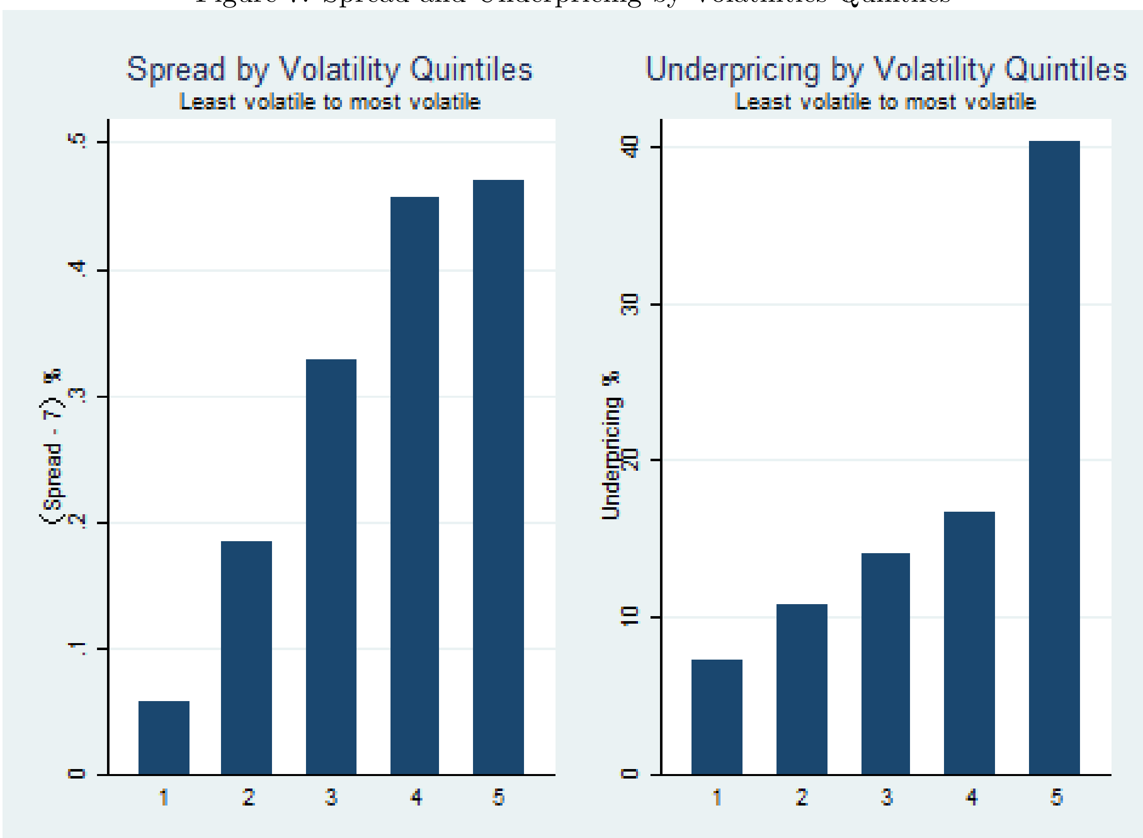


Figure 8: Spread and Underpricing by Volatilities Quintiles for Different Periods

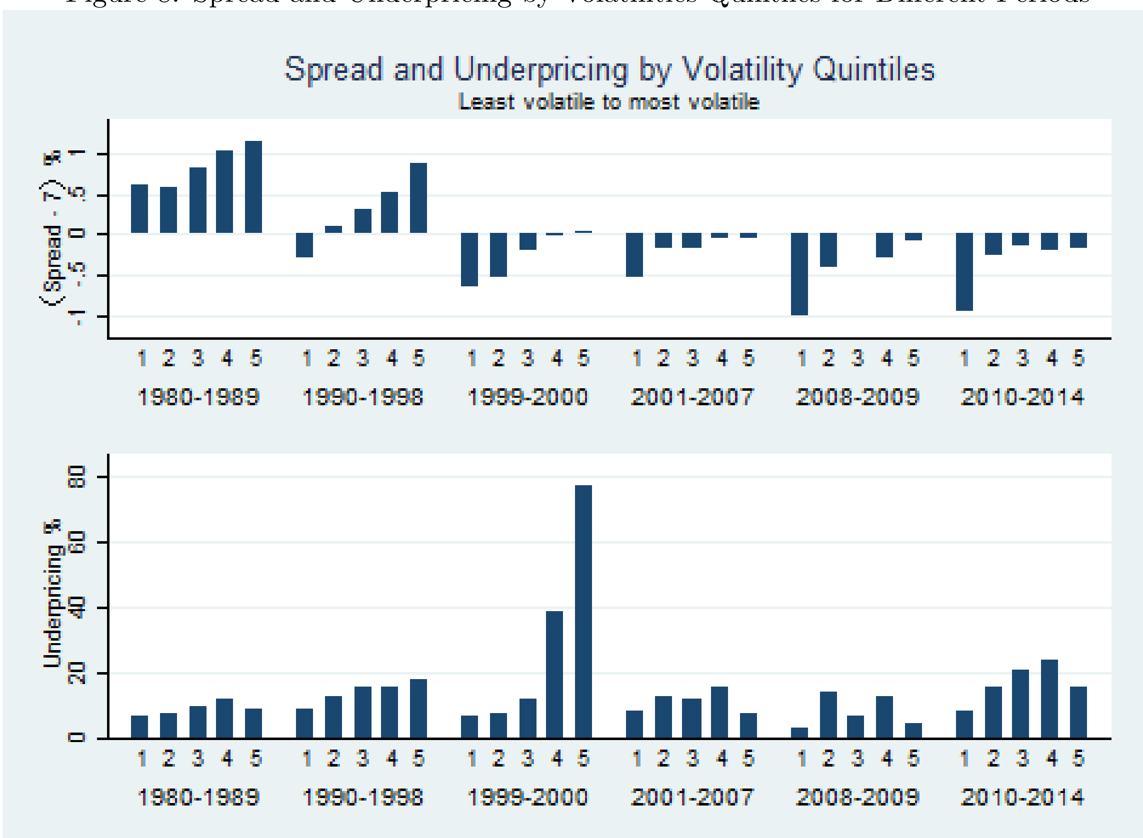


Figure 9: Frequency by Volatilities Quintiles for Different Periods

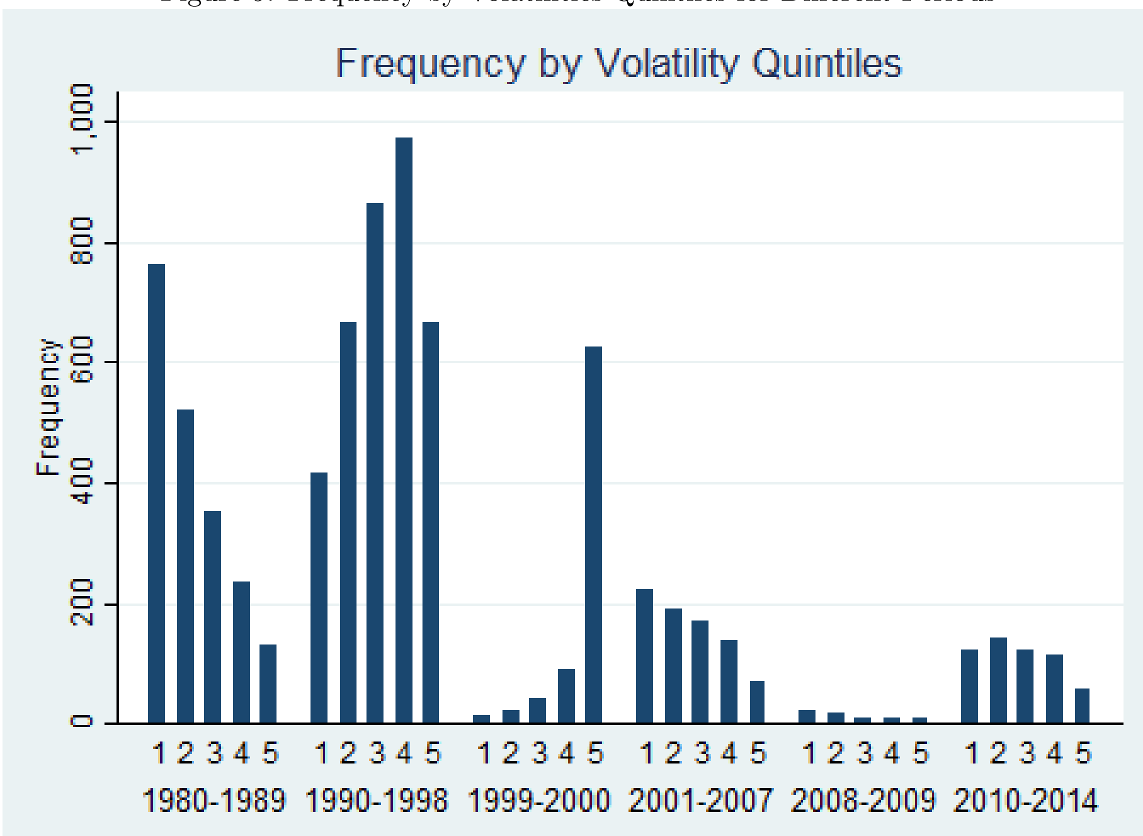


Figure 10: 1-Month(21 Trading Days) Holding Period Returns.

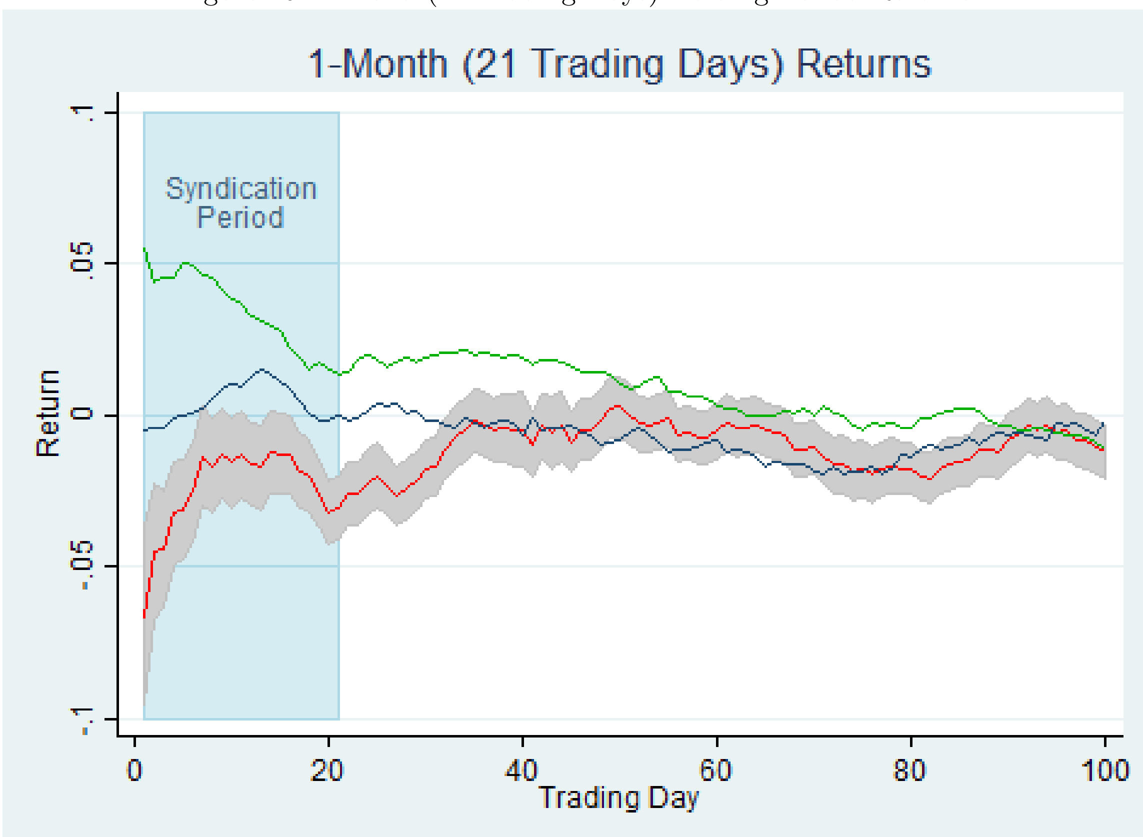


Figure 11: Institutional Holdings of IPOs.

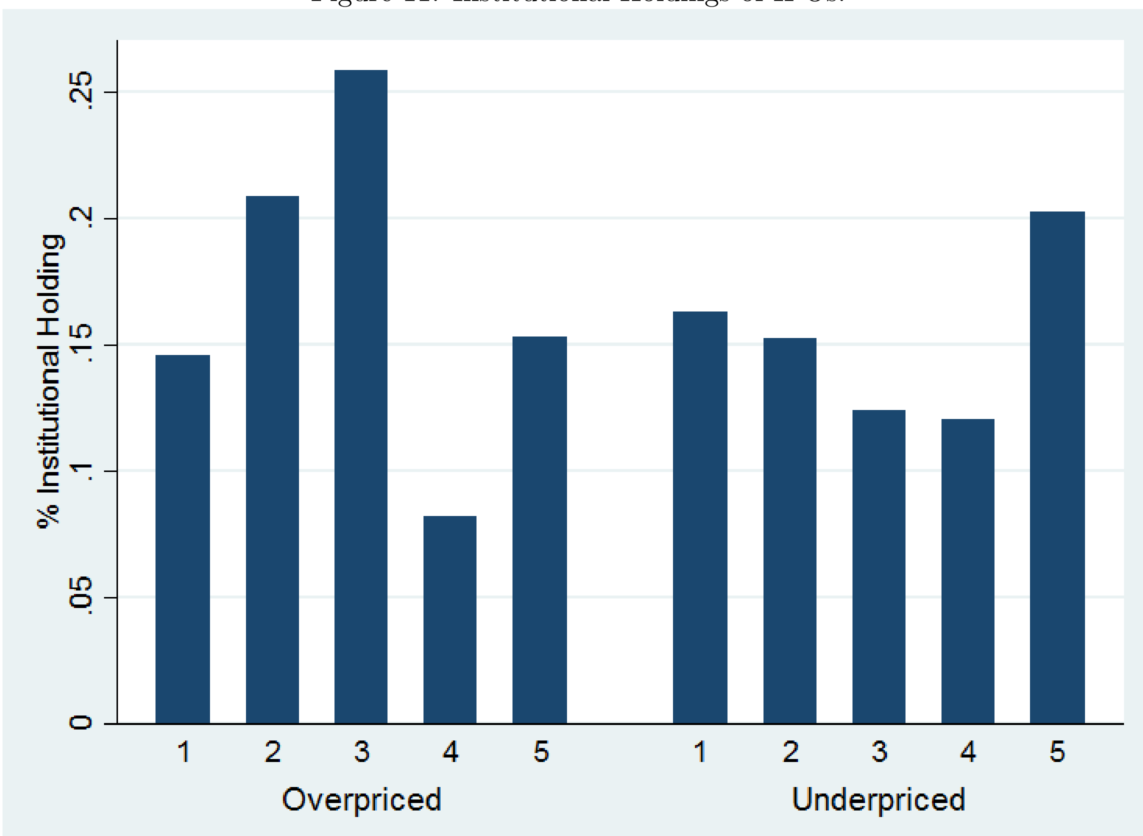


Table 1: Adoption of the UTSA by States

State	Year	State	Year
Alabama	1987	Montana	1985
Alaska	1988	Nebraska	1988
Arizona	1990	Nevada	1987
Arkansas	1981	New Hampshire	1990
California	1985	New Jersey	2012
Colorado	1986	New Mexico	1989
Connecticut	1983	New York	2017
Delaware	1982	North Carolina	1981
District of Columbia	1989	North Dakota	1983
Florida	1988	Ohio	1994
Georgia	1990	Oklahoma	1986
Hawaii	1989	Oregon	1988
Idaho	1981	Pennsylvania	2004
Illinois	1988	Rhode Island	1986
Indiana	1982	South Carolina	1992
Iowa	1990	South Dakota	1988
Kansas	1981	Tennessee	2000
Kentucky	1990	Texas	2013
Louisiana	1981	Utah	1989
Maine	1987	Vermont	1996
Maryland	1989	Virginia	1986
Massachusetts	2017	Washington	1982
Michigan	1998	West Virginia	1986
Minnesota	1981	Wisconsin	1986
Mississippi	1990	Wyoming	2006
Missouri	1995		

Table 2: Summary Statistics

Variable	Mean	SD	25%	50%	75%
Panel A: Innovation					
R&D Expenditure(Millions)	40.2	246.2	0.053	1.03	7.00
R&D to Asset(%)	6.36	15.5	0.21	2.33	7.28
R&D to Sales(%)	67.82	1890.3	0.20	2.08	7.58
Innovation(KPSS)	197.78	1761.5	0.37	2.15	17.09
Forward citations-weighted	60.02	261.4	3.07	8.50	28.59
Number of patents	27.57	121.51	1	4	13
Panel B: Performance and Risk					
EBITDA(Millions)	284.9	1987.4	-0.05	6.79	56.80
Sales(Millions)	927.4	5488	11.33	55.25	254.7
Stock Volatility(%)	3.98	3.19	2.04	3.19	4.94
Panel C: Competition & Collaboration					
Likelihood of having a same-industry M&A target	0.453	0.498	0.000	0.000	1.000
Likelihood of technology transfer in an alliance	0.135	0.342	0.000	0.000	1.000

Table 3: Effect of Protection on Industry-level Innovation (Market Capitalization-Weighted)

	Stock-Based		Citation-Weighted		Number of Patents	
	(1)	(2)	(3)	(4)	(5)	(6)
TS Protection (t-1)	-59.06	-42.75	-17.99**	-11.55*	-10.12**	-6.627**
	(-1.00)	(-0.86)	(-2.04)	(-1.93)	(-2.18)	(-2.06)
TS Protection (t-2)		-21.76		-8.736*		-4.656**
		(-0.98)		(-1.79)		(-1.98)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14643	14211	14643	14211	14643	14211
R^2	0.192	0.195	0.498	0.503	0.531	0.537

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 4: Effect of Protection on Industry-level Innovation (Equally Weighted)

	Stock-Based		Citation-Weighted		Number of Patents	
	(1)	(2)	(3)	(4)	(5)	(6)
TS Protection (t-1)	-7.570	-3.121	-5.425*	-4.122*	-3.439**	-2.286*
	(-0.67)	(-0.40)	(-1.78)	(-1.89)	(-2.00)	(-1.93)
TS Protection (t-2)		-6.160		-1.901		-1.574
		(-0.91)		(-0.90)		(-1.34)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14643	14208	14643	14208	14643	14208
R^2	0.258	0.262	0.477	0.475	0.517	0.518

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 5: Effect of Protection on Industry-level Innovation with Multiple Lags (Market Capitalization-Weighted)

	(1)	(2)	(3)	(4)
TS Protection (t-1)	-17.99**	-11.55*	-11.67**	-11.92**
	(-2.04)	(-1.93)	(-1.98)	(-2.03)
TS Protection (t-2)		-8.736*	-3.350**	-3.261**
		(-1.79)	(-2.04)	(-1.98)
TS Protection (t-3)			-7.234	-1.158
			(-1.21)	(-0.57)
TS Protection (t-4)				-8.145
				(-1.30)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	14643	14208	13778	13350
R^2	0.498	0.503	0.508	0.513

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 6: Effect of Protection on Innovation with High-tech Interaction (Market Capitalization-Weighted)

	(1) Stock Market-Weighted	(2) Citation-Weighted	(3) #Patents
TS Protection (t-1)	-37.00	-7.693***	-4.251***
	(-1.32)	(-2.84)	(-3.30)
TS Protection (t-2)	-23.24	-9.479***	-5.482***
	(-1.29)	(-3.44)	(-4.13)
TS Protection(t-1) × HiTech	-53.55	-35.88**	-22.14**
	(-0.90)	(-2.20)	(-2.36)
TS Protection(t-2) × HiTech	15.12	7.796	8.203
	(0.28)	(0.51)	(0.94)
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Observations	14208	14208	14208
R^2	0.195	0.504	0.538

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 7: Effect of Protection on Innovation with High-tech Interaction (Equally Weighted)

	(1) Stock Market-Weighted	(2) Citation-Weighted	(3) #Patents
TS Protection (t-1)	-0.725	-3.145**	-1.690**
	(-0.16)	(-2.06)	(-2.13)
TS Protection (t-2)	-8.623*	-2.203	-1.809**
	(-1.85)	(-1.43)	(-2.21)
TS Protection(t-1) × HiTech	-27.67*	-10.92	-6.691*
	(-1.66)	(-1.61)	(-1.74)
TS Protection(t-2) × HiTech	28.50*	3.977	2.985
	(1.76)	(0.62)	(0.82)
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Observations	14208	14208	14208
R^2	0.262	0.476	0.519

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 8: Effects of Trade Secret Protection on Competitor

	(1) Stock Market-Based	(2) Citation-Weighted	(3) #Patents
Competitor TS Protection (t-1)	-1351.2	-57.76**	-28.81**
	(-1.46)	(-2.13)	(-2.16)
Firm Fixed Effects	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	1957	1957	1957
R^2	0.177	0.232	0.276

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 9: Mechanism

	(1) Tech Transfer	(2) Same-Industry M&A(Public)	(3) Same-Industry M&A(All)
Treated × After	0.030**	0.138***	0.008
	(2.23)	(5.33)	(0.68)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	218799	17102	793370
R^2	0.509	0.975	0.721

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 10: Firm-level Number of Patents

	(1) Stock-based	(2) Citation-weighted	(3) Number of patents
Treated × After	-12.36	1.293	0.305
	(-0.89)	(0.50)	(0.24)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	40801	40801	40801
R^2	0.574	0.895	0.889

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 11: Industry Concentration

	Equally-Weighted			Market Cap-Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
	HHI	HHI	HHI	HHI	HHI	HHI
EW Protection(t)	0.00496	0.0219	0.0243			
	(0.44)	(1.14)	(1.25)			
EW Protection (t-1)		-0.0180	0.00114			
		(-0.95)	(0.05)			
EW Protection (t-2)			-0.0244			
			(-1.31)			
MCW Protection(t)				0.000120	0.0143	0.0157
				(0.01)	(1.08)	(1.17)
MCW Protection (t-1)					-0.0151	-0.0127
					(-1.18)	(-0.73)
MCW Protection (t-2)						-0.00169
						(-0.11)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15075	14643	14208	15075	14643	14208
R^2	0.414	0.415	0.415	0.414	0.415	0.415

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 12: Firm-level Regressions

	(1) log(EBITDA)	(2) log(Sales)	(3) Stock Volatility
Treated × After	0.123***	0.099***	-0.1274**
	(3.48)	3.71	(-2.52)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	128016	228962	169286
R^2	0.935	0.955	0.751

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 13: Industry-level Innovation with Controls (Market Cap-Weighted)

	(1) Stock-based	(2) Citation-Weighted	(3) #Patents
TS Protection (t-1)	-66.97**	-13.74***	-6.908***
	(-2.49)	(-5.07)	(-5.23)
Non-compete Controls	Yes	Yes	Yes
Bank Regulation Controls	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	14211	14211	14211
R^2	0.195	0.503	0.538

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 14: Industry-level Innovation with Controls (Equally Weighted)

	(1) Stock-based	(2) Citation-Weighted	(3) #Patents
TS Protection (t-1)	-0.698	-3.997**	-1.782**
	(-0.18)	(-2.43)	(-2.52)
Non-compete Controls	Yes	Yes	Yes
Bank Regulation Controls	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	11241	11241	11241
R^2	0.281	0.435	0.467

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 15: Robustness Check: Excluding Top Industries

2-Digit SIC	2-Digit SIC Name	Percentage	Coefficient Estimate	
			Citation-weighted	# Patents
35	Industrial Machinery & Equipment	7.38	-8.513	-6.001
36	Electronic & Other Electric Equipment	5.12	-15.095	-9.086
73	Business Services	5.06	-17.647	-9.942
50	Wholesale Trade Durable Goods	4.75	-18.488	-10.285
20	Food & Kindred Products	4.44	-19.100	-10.739
38	Instruments & Related Products	4.23	-13.615	-7.027
28	Chemical & Allied Products	4.07	-17.982	-9.645
34	Fabricated Metal Products	3.16	-18.538	-10.415
37	Transportation Equipment	2.94	-18.442	-10.147
27	Printing & Publishing	2.47	-18.347	-10.327
33	Primary Metal Industries	2.47	-18.625	-10.450
51	Wholesale Trade Nondurable Goods	2.46	-18.318	-10.298
80	Health Services	2.43	-18.251	-10.257
48	Communications	2.09	-20.291	-11.009
39	Miscellaneous Manufacturing Industries	2.07	-18.329	-10.308
59	Miscellaneous Retail	2.06	-18.186	-10.224
32	Stone, Clay, & Glass Products	2.02	-18.405	-10.609
61	Nondepository Institutions	2.02	-18.303	-10.301
87	Engineering & Management Services	2.02	-18.224	-10.257

Table 16: Comparative Statics Summary

	Uncertainty (σ)	Loss share (β)	Profit Share (γ)
Offer Price (p^*)	$\downarrow$	$\downarrow$	$\uparrow$
Fee (k)	$\uparrow$	$\downarrow$	$\uparrow$
Issuer Payoff	$\downarrow$	$\downarrow$	$\downarrow$
Underwriter Payoff	$\uparrow$	$\downarrow$	$\uparrow$

Table 17: IPO Summary Statistics

	Mean	Median	Standard Deviation	Minimum	Maximum
Gross Spread	7.31	7.00	1.19	0.22	20.00
1st Day Return	17.73	6.25	39.79	-89.08	697.50
Size(in millions)	86.23	32.00	356.65	0.15	16006.88
Volatility	4.05	3.59	2.10	0.00	20.63
% Underpriced	74.07	100.00	43.83	0.00	100.00
Observations	8126				

Table 18: IPO Summary Statistics by Period

	1980-1989	1990-1998	1999-2000	2001-2007	2008-2009	2010-2014
Gross Spread	7.733	7.374	6.974	6.759	6.526	6.632
	(1.187)	(1.210)	(0.703)	(0.788)	(0.843)	(0.852)
1st Day Return	7.873	14.46	66.13	10.99	7.717	16.15
	(16.84)	(25.67)	(90.57)	(18.68)	(17.33)	(26.73)
Size(in millions)	25.44	56.43	119.4	183.5	277.9	261.5
	(73.52)	(170.5)	(292.0)	(403.8)	(342.5)	(1001.0)
Volatility	3.039	4.150	7.271	3.344	3.486	3.597
	(1.507)	(1.691)	(2.547)	(1.518)	(2.020)	(1.629)
% Underpriced	70.69	73.01	82.07	71.90	61.90	70.52
	(45.53)	(44.40)	(38.38)	(44.98)	(48.95)	(45.63)
Observations	1982	3546	792	783	63	553

Table 19: Volatility and Underpricing

	(1)	(2)	(3)	(4)	(5)	(6)
Volatility	8.357***	4.889***	8.357***	4.889***	4.207**	1.318
	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)	(0.380)
Size(in millions)	0.215***	0.229***	0.215***	0.229***	-0.0611	-0.0446
	(0.000)	(0.000)	(0.000)	(0.000)	(0.498)	(0.577)
Size $\times$ Volatility					0.0589**	0.0547*
					(0.047)	(0.054)
Constant	-25.44***	-14.34***	-25.44***	-14.34***	-6.385	-0.475
	(0.000)	(0.001)	(0.000)	(0.001)	(0.292)	(0.943)
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Observations	3965	3965	3965	3965	3965	3965

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 20: Parameter Estimation Result

	No Restriction		With Restrictions	
	Mean	Standard Deviation	Mean	Standard Deviation
β	0.519	0.0201	0.512	0.0712
γ	-0.0385	0.0051	0.000	0.0415
Volatility Multiple	4.140	0.144	3.10	0.0322

Table 21: Parameter Calculation Result

	Multiple = 4.14		Multiple = 3.10	
	Mean	Standard Deviation	Mean	Standard Deviation
β	0.518	0.0231	0.406	0.173
γ	-0.0382	0.0577	-0.0102	0.0436

APPENDIX

A.1. Offer Price and Fee when $\gamma > k > \beta$

Proof. The underwriter chooses p_H^* over p_L^* when

$$k_H p_H - k_L p_L + (\gamma - \beta)\left(F(p_H)p_H - F(p_L)p_L - \int_{p_L}^{p_H} xf(x)dx\right) - \gamma(p_H - p_L) > 0 \quad \text{(A.1)}$$

where k_H and k_L are the fees selected by the issuer when the offer price is p_H^* or p_L^* respectively. The issuer prefers p_H^* to p_L^* if

$$p_H^*(1 - k_H) > p_L^*(1 - k_L) = \underline{p} \quad \text{(A.2)}$$

To maximize her chance of getting more than her reservation price[1], the issuer will set the fee equal to zero if she is only getting $\underline{p}$. Setting $k_L =$ and combining (A.1) and (A.2) yields

$$\bar{p} - \underline{p} > -\frac{\gamma - \beta}{1 - \gamma}\left(F(\bar{p})\bar{p} - F(\underline{p})\underline{p} - \int_{\underline{p}}^{\bar{p}} xf(x)dx\right) \quad \text{(A.3)}$$

Notice that the part in the parenthesis can be rearranged into

$$F(\underline{p})(\bar{p} - \underline{p}) + \int_{\underline{p}}^{\bar{p}} (\bar{p} - x)f(x)dx > 0 \quad \text{(A.4)}$$

Thus, Condition (A.3) always holds. The issuer sets the fee just high enough for the underwriter to choose p_H^* instead of p_L^* i.e. (A.1) is equal to zero.

$$k^* = \frac{\bar{p} - \underline{p}}{\bar{p}}\gamma - \frac{\gamma - \beta}{\bar{p}}\left(F(\bar{p})\bar{p} - F(\underline{p})\underline{p} - \int_{\underline{p}}^{\bar{p}} xf(x)dx\right) \quad \text{(A.5)}$$

and

$$p^* = \bar{p} \quad \text{(A.6)}$$

[1](A.1) is more likely to satisfy when k_L is small.

$\square$

A.2. Proof of Proposition 2 and Lemma 1

Proof. We want to show that the offer price is less than the expected value of market price, or

$$p^* = exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\mu\right) < exp\left(\mu+\frac{\sigma^2}{2}\right) \tag{A.7}$$

Hence, a sufficient but not necessary condition for A.7 to hold is that $\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) < 0$. Recall the issuer's FOC

$$\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right) = \left(\frac{1-k^*}{\beta-\gamma}\right)\sigma \tag{A.8}$$

Notice that $\frac{k^*-\gamma}{\beta-\gamma} = 0.5$ or equivalently $k^* = \frac{\beta+\gamma}{2}$ when $\sigma = \sqrt{\frac{2}{\pi}}\left(\frac{\beta-\gamma}{2-\beta-\gamma}\right)$. Furthermore, $\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) \leq 0$ when $\frac{k^*-\gamma}{\beta-\gamma} \leq 0.5$. Assumption 1 states that

$$\sigma < \sqrt{\frac{2}{\pi}}\left(\frac{\beta-\gamma}{2-\beta-\gamma}\right) \equiv \bar{\sigma}$$

If k^*, and henceforth $\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)$, decreases as σ decreases, then $\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) < 0$ for $\sigma < \bar{\sigma}$ and the proof will be complete. $\frac{dk^*}{d\sigma}$ can be obtained by implicit differentiation of (A.8) with respect to σ

$$\frac{1-k^*}{\beta-\gamma} - \frac{dk^*}{d\sigma}\frac{\sigma}{\beta-\gamma} = -\frac{1}{\beta-\gamma}\frac{dk^*}{d\sigma}\phi'\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)\frac{1}{\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)} \tag{A.9}$$

$$\frac{dk^*}{d\sigma} = \frac{1-k^*}{\sigma-\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)} \tag{A.10}$$

When $\sigma = \bar{\sigma}$, we know that $\frac{dk^*}{d\sigma}\Big|_{\sigma=\bar{\sigma}} = \frac{1-k^*}{\sigma} > 0$. Now assume that $\sigma_1 = \bar{\sigma} - \epsilon$ where ϵ is extremely small. Since $\frac{dk^*}{d\sigma}\Big|_{\sigma=\bar{\sigma}} > 0$, $k_1^* = \frac{\beta+\gamma}{2} - \xi$ where ξ is small. Therefore

$$\Phi^{-1}\left(\frac{k_1^* - \gamma}{\beta - \gamma}\right) = \Phi^{-1}\left(\frac{1}{2} - \frac{\xi}{\beta - \gamma}\right) < 0 \tag{A.11}$$

and $\frac{dk^*}{d\sigma}\Big|_{\sigma=\bar{\sigma}-\epsilon} > 0$. Repeating the steps above and we have proved that $\frac{dk^*}{d\sigma} > 0$ and $\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) < 0$ for all $\sigma < \bar{\sigma}$.

$\square$

A.3. Proof of Proposition 3

Proof. Differentiate the expression of the price A.7 with respect to σ as well

$$\frac{dp^*}{d\sigma} = \left(\frac{\sigma}{(\beta-\gamma)\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}\frac{dk^*}{d\sigma} + \Phi^{-1}(\frac{k^*-\gamma}{\beta-\gamma})\right) exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) + \mu\right) \tag{A.12}$$

Substituting (A.10) into (A.12) yields

$$\frac{dp^*}{d\sigma} = \left(\frac{\sigma}{(\beta-\gamma)\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}\frac{1-k^*}{\sigma - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)} + \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right) exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) + \mu\right) \tag{A.13}$$

For $\frac{dp^*}{d\sigma}$ to be negative, it must be true that

$$\frac{\sigma}{(\beta-\gamma)\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}\frac{1-k^*}{\sigma - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)} + \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) < 0 \tag{A.14}$$

Substituting (A.8) into (A.14) to simplify the above expression to

$$\frac{1}{\sigma - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)} + \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) < 0 \tag{A.15}$$

Take second derivative of p^* with respect to σ,

$$\frac{d^2p^*}{d\sigma^2} = \left(\frac{1}{\sigma - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)} + \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)^2 exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\mu\right)$$
$$+\frac{1}{\sigma - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)}\left(1 - \frac{1}{\sigma - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)} + \frac{1}{\left(\sigma - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)^2}\right) exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\mu\right) \tag{A.16}$$

We can see from A.16 that $\frac{d^2p^*}{d\sigma^2} > 0$ since $\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) < 0$. As $\sigma \to 0$, $k^* \to \gamma$, and $\frac{dp^*}{d\sigma} < 0$. In addition, when $\sigma = \bar{\sigma}$, $\frac{dp^*}{d\sigma} = \frac{1}{\bar{\sigma}} > 0$. Therefore, there exists an $\hat{\sigma}$ such that

$$\frac{1}{\hat{\sigma} - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)} + \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) = 0 \tag{A.17}$$

And price increases with uncertainty when $\sigma > \hat{\sigma}$ but decreases with uncertainty when $\sigma < \hat{\sigma}$.

□

A.4. Proof of Lemma 3

Proof. Recall that the payoff to the underwriter is

$$kp^* + \beta\left(\int_{-\infty}^{p^*} xf(x)dx - F(p^*)p^*\right) + \gamma\left(\int_{p^*}^{\infty} xf(x)dx - (1-F(p^*))p^*\right) \tag{A.18}$$

Implicitly differentiate (A.18) to obtain

$$\frac{dk*}{d\sigma}p^* + \frac{dp*}{d\sigma}\left(k - \gamma - F(p^*)(\beta-\gamma)\right) = \frac{dk*}{d\sigma}p^* > 0$$

□

A.5. Proof of Proposition 4

Proof. Differentiate A.8 with respect to β

$$\phi'\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)\frac{\frac{dk^*}{d\beta}\frac{1}{\beta-\gamma}-\frac{k-\gamma}{(\beta-\gamma)^2}}{\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}=\left(-\frac{dk^*}{d\beta}\frac{1}{\beta-\gamma}-\frac{1-k^*}{(\beta-\gamma)^2}\right)\sigma \tag{A.19}$$

Simplifying and rearranging A.19

$$\begin{aligned}\frac{dk^*}{d\beta}&=-\frac{1}{\sigma-\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)}\left(\frac{k^*-\gamma}{\beta-\gamma}\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\frac{(1-k^*)\sigma}{(\beta-\gamma)}\right)\\&=-\frac{1}{\sigma-\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)}\left(\frac{k^*-\gamma}{\beta-\gamma}\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)\right)\end{aligned} \tag{A.20}$$

The first term in A.20 is negative since σ and $-\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)$ are both positive. It remains to prove that the equation in the form of $a\Phi^{-1}(a)+\phi(\Phi^{-1}(a))$ is positive. $a\Phi^{-1}(a)+\phi(\Phi^{-1}(a))=0$ when $a=0$. Its first derivative is $\frac{a}{\phi(\Phi^{-1}(a))}>0$. Thus, the second term in A.20 is positive and the entire expression is negative. □

A.6. Proof of Proposition 5

Proof. Differentiate A.7 with respect to β

$$\frac{dp^*}{d\beta}=exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\mu\right)\frac{\sigma}{(\beta-\gamma)\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}\left(\frac{dk^*}{d\beta}-\frac{k-\gamma}{\beta-\gamma}\right) \tag{A.21}$$

A.21 is negative since $\frac{dk^*}{d\beta}<0$. Therefore, $\frac{dk^*}{d\beta}<0$ and fees increase when the underwriter bears more losses. □

A.7. Proof of Proposition 6

Proof. Recall that the payoff to the underwriter is

$$kp^* + \beta \left(\int_{-\infty}^{p^*} xf(x)dx - F(p^*)p^* \right) + \gamma \left(\int_{p^*}^{\infty} xf(x)dx - (1 - F(p^*))p^* \right) \tag{A.22}$$

Differentiate (A.22) to obtain

$$\begin{aligned} &\frac{dk^*}{d\beta}p^* + \frac{dp^*}{d\beta}\left(k^* - \gamma - F(p^*)(\beta - \gamma)\right) + \left(\int_{-\infty}^{p^*} xf(x)dx - F(p^*)p^* \right) \\ =&\frac{dk^*}{d\beta}p^* + \left(\int_{-\infty}^{p^*} xf(x)dx - F(p^*)p^* \right) \end{aligned}$$

Since $\frac{dk^*}{d\beta} < 0$ and $\int_{-\infty}^{p^*} xf(x)dx - F(p^*)p^* < 0$, the underwriter's payoff decreases in loss share. □

A.8. Proof of Proposition 7

Proof. Recall that the payoff to the issuer is

$$p^*(1 - k^*) \tag{A.23}$$

Differentiate it with respect to β obtain

$$\frac{dp^*}{d\beta}(1 - k) - \frac{dk^*}{d\beta}p^* \tag{A.24}$$

Substitute A.21 into A.24,

$$exp\left(\sigma\Phi^{-1}\left(\frac{k^* - \gamma}{\beta - \gamma}\right) + \mu\right)\left(\left(\frac{\sigma(1 - k^*)}{(\beta - \gamma)\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)} - 1\right)\frac{dk^*}{d\beta} - \frac{\sigma(1 - k^*)(k^* - \gamma)}{(\beta - \gamma)^2\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}\right) \tag{A.25}$$

Reduce A.25 using A.8 to

$$exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\mu\right)\left(-\frac{\sigma(1-k^*)(k^*-\gamma)}{(\beta-\gamma)^2\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}\right)<0 \tag{A.26}$$

$\square$

A.9. Proof of Proposition 8

Proof. Differentiate A.8 with respect to γ

$$\phi'\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)\frac{\frac{dk^*}{d\gamma}\frac{1}{\beta-\gamma}-\frac{1}{\beta-\gamma}+\frac{k-\gamma}{(\beta-\gamma)^2}}{\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}=\left(-\frac{dk^*}{d\gamma}\frac{1}{\beta-\gamma}+\frac{1-k^*}{(\beta-\gamma)^2}\right)\sigma \tag{A.27}$$

Simplifying and rearranging A.27

$$\begin{aligned}\frac{dk^*}{d\gamma}=&\frac{1}{\sigma-\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)}\left(\frac{k^*-\gamma-\beta+\gamma}{\beta-\gamma}\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\frac{(1-k^*)\sigma}{(\beta-\gamma)}\right)\\=&\frac{1}{\sigma-\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)}\left(\frac{k^*-\beta}{\beta-\gamma}\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\frac{(1-k^*)\sigma}{(\beta-\gamma)}\right)\end{aligned} \tag{A.28}$$

The first term in A.28 is positive since σ and $-\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)$ are both positive. The second term in A.28 is positive since $\frac{k^*-\beta}{\beta-\gamma}<0$ and $\frac{(1-k^*)\sigma}{(\beta-\gamma)}>0$. Therefore, the derivative is positive. $\square$

A.10. Proof of Proposition 9

Proof. Differentiate A.7 with respect to γ

$$\frac{dp^*}{d\gamma}=exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)+\mu\right)\frac{\sigma}{(\beta-\gamma)\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}\left(\frac{dk^*}{d\gamma}-1+\frac{k-\gamma}{\beta-\gamma}\right) \tag{A.29}$$

The first two terms in A.29 are positive, so let us focus on the last term.

$$\frac{dk^*}{d\gamma} - 1 + \frac{k-\gamma}{\beta-\gamma} = \frac{1}{\sigma - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)} \left(\frac{k^*-\beta}{\beta-\gamma}\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) + \frac{(1-k^*)\sigma}{(\beta-\gamma)}\right) - 1 + \frac{k-\gamma}{\beta-\gamma} \tag{A.30}$$

$$= \frac{1}{\left(\sigma - \Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)(\beta-\gamma)}(1-\beta)\sigma > 0 \tag{A.31}$$

Note that $\frac{dp^*}{d\gamma} = 0$ when $\beta = 1$. □

A.11. Proof of Proposition 10

Proof. Recall that the payoff to the underwriter is

$$kp^* + \beta\left(\int_{-\infty}^{p^*} xf(x)dx - F(p^*)p^*\right) + \gamma\left(\int_{p^*}^{\infty} xf(x)dx - (1-F(p^*))p^*\right) \tag{A.32}$$

Differentiate (A.32) to obtain

$$\begin{aligned} &\frac{dk^*}{d\gamma}p^* + \frac{dp^*}{d\gamma}\left(k^* - \gamma - F(p^*)(\beta-\gamma)\right) + \left(\int_{p^*}^{\infty} xf(x)dx - (1-F(p^*))p^*\right) \\ =&\frac{dk^*}{d\gamma}p^* + \left(\int_{p^*}^{\infty} xf(x)dx - (1-F(p^*))p^*\right) \end{aligned}$$

Since $\frac{dk^*}{d\gamma} > 0$ and $\int_{p^*}^{\infty} xf(x)dx - (1-F(p^*))p^* > 0$, the underwriter's payoff decreases in loss share. □

A.12. Proof of Proposition 11

Proof. The first derivative of the issuer's payoff with respect to profit share is

$$exp\left(\sigma\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right) + \mu\right)\left(\left(\frac{\sigma}{(\beta-\gamma)\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)} - 1\right)\frac{dk^*}{d\gamma} + \frac{(1-k)(k-\beta)\sigma}{(\beta-\gamma)^2\phi\left(\Phi^{-1}\left(\frac{k^*-\gamma}{\beta-\gamma}\right)\right)}\right) \tag{A.33}$$

Substitute A.8 into A.33

$$exp\left(\sigma\Phi^{-1}\left(\frac{k^{*}-\gamma}{\beta-\gamma}\right)+\mu\right)\left(\frac{(1-k)(k-\beta)\sigma}{(\beta-\gamma)^{2}\phi\left(\Phi^{-1}\left(\frac{k^{*}-\gamma}{\beta-\gamma}\right)\right)}\right)<0$$

$\square$

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