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Essays on the Role of Reputation in the Markets for Technology

Mahendiran Shreekanth

UNIL | Université de Lausanne

FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT STRATÉGIE, GLOBALISATION ET SOCIÉTÉ

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THÈSE DE DOCTORAT

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pour l'obtention du grade de
Doctorat en Management

par

Shreekanth MAHENDIRAN

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Faculté des hautes études commerciales
Internef - 261
CH-1015 Lausanne

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Shreekanth MAHENDIRAN

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sans se prononcer sur les opinions exprimées dans cette thèse.

Lausanne, le 25.04.2024

Professeure Marianne Schmid Mast, Doyenne

Thesis Committee

Prof. Jean-Philippe Bonardi,

University of Lausanne, Switzerland

Thesis Supervisor

Prof. Chirantan Chatterjee,

University of Sussex Business School, United Kingdom

Thesis Co-supervisor

Prof. Giorgio Zanarone,

University of Lausanne, Switzerland

Internal Expert

Prof. Gary Dushnitsky,

London Business School, United Kingdom

External Expert

University of Lausanne
Faculty of Business and Economics

Ph.D. in Management

I hereby certify that I have examined the doctoral thesis of

Shreekanth MAHENDIRAN

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: Date: 14.04.2024

Prof. Jean-Philippe BONARDI
Thesis supervisor

University of Lausanne
Faculty of Business and Economics

Ph.D. in Management

I hereby certify that I have examined the doctoral thesis of

Shreekanth MAHENDIRAN

and have found it to meet the requirements for a doctoral thesis.
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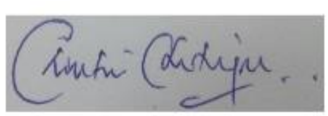
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature:  Date: 18/04/2024

Prof. Chirantan CHATTERJEE
Co-supervisor

University of Lausanne
Faculty of Business and Economics

Ph.D. in Management

I hereby certify that I have examined the doctoral thesis of

Shreekanth MAHENDIRAN

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: ______________________ Date: 17/4/2024

Prof. Giorgio ZANARONE
Internal expert

University of Lausanne
Faculty of Business and Economics

Ph.D. in Management

I hereby certify that I have examined the doctoral thesis of

Shreekanth MAHENDIRAN

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: Gary Dushnitsky Date: 17.4.2024

Prof. Gary DUSHNITSKY
External expert

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Contents

Synthesis of the Dissertation

1 Introduction

There is a large literature that explores several elements concerning the markets for technology (Arora, Fosfuri, & Gambardella ,2004). Among these, many scholars have examined the role of reputation in the financing of innovative ventures (Chahine, Filatotchev, Bruton, & Wright ,2021; Nahata ,2008), shaping corporate innovation activities (Galasso & Luo ,2021, 2022), retainment of tacit knowledge (Agarwal, Ganco, & Ziedonis ,2009), make or buy decisions (Dollinger, Golden, & Saxton ,1997), strategies concerning intellectual property rights (Gans & Ryall ,2017; James, Leiblein, & Lu ,2013), signaling trust to external stakeholders (Hurwitz & Caves ,1988; Mendonça, Pereira, & Godinho ,2004) and others. The importance of reputation has found a resurgence among scholars as technological advancements, such as digital platforms, cryptocurrency, artificial intelligence, and others, offer new competitive dynamics to firms (Bolton, Greiner, & Ockenfels ,2013; Kokkodis & Ipeirotis ,2016; Rossi ,2024.

Building on this extensive work, I explore whether the reputational dynamics between different types of firms influence entrepreneurial and innovative outcomes. To explain, every market constitutes both established firms with incentives to build a particular kind of reputation and extract economic returns in the long run; and entrants whose primary motive is to extract as much economic returns as possible in the short run. Technological advancements have considerably reduced the barriers to entry therefore not only fostering business activities but has also provided conditions for opportunistic individuals to enter the market to capitalize upon market opportunities, earn financial rewards, and exit thereupon.

While established firms can commit to long-run objectives, the presence of firms with short-term objectives can cause unfavorable outcomes for the entire market (Ely, Fudenberg, & Levine ,2008). An investigation into such reputational dynamics will shed a deeper understanding of the negative impact of a bad reputation and whether it is contained within a particular market or spans across boundaries such as technologies, sectors, geography, and others. Additionally, these reputational dynamics can have heterogeneous impacts in different stages of the markets for technology.

In light of this, my thesis is structured to facilitate an investigation into my research question within the contexts of financing and commercialization stages of innovation. The first paper examines how firms that invest efforts in the commercialization of innovation through trademarks protect their market from infringers. This setting of pharmaceutical industry in the Indian market provides an excellent opportunity to understand the non-market strategies adopted by incumbent trademark holders, building a tough reputation, to overcome the value-destroying activities by infringers in the market.

The second and third paper is set within the context of financing innovation - the entrepreneurial landscape to be particular. The second paper investigates whether misconduct allegations against startups can result in negative outcomes for technologically similar innocent startups. New and innovative technologies hold the potential to attract opportunistic individuals who aim to capitalize on the informational asymmetry and hot market conditions. The entry by such opportunistic individuals increases the prospects of misconduct allegations which can have adverse consequences for other innocent startups developing similar technology. Our findings provide support for this intuition. In addition, we find that reputational concerns of non-VCs and less-experienced investors contribute significantly to the negative financing outcomes for other innocent startups.

The third paper examines the evolution of investors' networks over time. It is important to note that this paper leverages misconduct allegations as an external reputational shock to understand how the syndication networks change over time. The paper primarily concerns itself with understanding the evolution of relationships between investors in their syndication network. Interestingly, this study reveals the resilience of investors' networks to such shocks wherein co-investors tend only to reduce their co-investment amounts in syndicating deals with the tainted investors, but not necessarily terminate their ties with them.

2 Paper 1 - Role of tough reputation in deterring trademark infringement

Firms invest considerable resources in research and development efforts to develop novel innovative technologies, or even recombine older technologies in novel ways to cater to emerging market segments. In addition to this, firms undertake significant investment to transform these novel technologies into downstream products that meet the requirements of final consumers. Under ideal scenario, firms launch their products and are able to successfully extract economic returns by competing in the market. However, there are market imperfections which necessiate firms to develop trademarks that convey quality of their products, especially in the context of credence goods, and develop brand loyalty to continue to generate revenue in the long run. Consequently, trademark occupies the core of any successful brand acting as a fundamental identifier that consumers associate with quality and trust. Given its significance, competitors can try to free-ride upon the incumbent's trademark to capture value from the market without making the necessary initial investments in creating their own trademark or developing brand loyalty. Thus, firms are deeply concerned with protection of their trademark which becomes more pronounced in markets where legal protections may be insufficient.

Over the centuries, governments in many countries have been refining its regulations and judicial systems to ensure that the firm's exclusive rights over their intellectual property is protected. However, the effectiveness of such protection can vary widely depending upon the legal and enforcement landscape. In jurisdictions with robust legal systems, trademark holders can consistently rely on courts to uphold their rights and penalize any infringement activities by competitors. However, in jurisdictions with weaker legal enforceemnt, infringement remains a prevalent issue which has become more pronounced with the rapid shift in consumers accessing digital platforms to purchase products, rather than traditional retail shops. While extant literature have highlighted the substitution and complementary effect of imitation/infringement, the presence of such actors in pharmaceutical industries can actually be value-destroying and welfare-reducing in nature as consumers are not only deceived by the trademark infringers but also face health risks by consuming potentially lower-quality medicinal products.

In this paper, my co-authors and I investigate how firms can protect their market from infringement in weak IPR regimes - especially since trademark registration may not be sufficient to deter infringement. Our mechanism relies upon firms developing a tough reputation by pursuing litigation against trademark infringement. We theorize that such actions can signal a firm's commitment to protect their brand integrity and potentially discourage future infringement by infringers. We implement an instrumental-variable estimation strategy to make causal claims on the impact of tough reputation on the measures of infringement. The findings reveal that the future infringement reduces as firms develop a tough reputation against trademark infingement. Interestingly, we find that firm's tough reputation induces competitors to name their subsequent trademarks much more differently, thereby reducing any prospect of legal confrontation emanating from trademark infringement. In addition, our results reveal that firm with tough reputation experience of lower risk of being infringed in the future, as the quantum of infringing trademarks in the market reduces subsequent to litigations against infringers. More importantly, we find that this deterrence effect is stronger in lucrative markets, thereby implying that tough reputation confers protection to the core market of an incumbent. In sum, these results highlight the importance of litigation as a deterrent against infringement and underscores the challenges firms face in protecting their trademarks in regions with weaker legal enforcement.

Broadly, this study underscore the importance of proactive trademark protection measures and strategic use of litigation to defend brand integrity and market position in challenging legal environments. This aspect becomes critical as companies continue to navigate the complexities of global markets. Firms will have to continue its efforts in understanding and effectively managing trademark protection strategies will remain essential for sustaining competitive advantage and preserving brand value.

3 Paper 2 - Role of investors' reputation in propagating negative effects of misconduct allegations

Entrepreneurs and investors are continually grappling with the unpredictable nature of financing opportunities, a challenge that is increasingly daunting for innovative and risky startups. The landscape of external finance remains subject to the ebbs and flow of market conditions despite the considerable overall increase in investment from venture capitalists in recent decades (Nanda & Rhodes-Kropf ,2017). Recent years have witnessed a significant uptick in misconduct allegations targeting entrepreneurial ventures. These allegations, even if unproven, can profoundly impact the performance of innocent startups. While these allegations may serve as cautionary signals of industry risks, they could deter investment and cast a shadow of suspicion over the entire sector (Naumovska & Zajac ,2022; Paruchuri & Misangyi ,2015). For instance: the highly public collapse of FTX following allegations by competitor Binance. This event not only destroyed investor confidence but also provoked scrutiny over governance practices and investor protection. The fallout from the Theranos scandal is another example that not only attracted scrutiny over governance practices but highlighted the impact of such misconduct allegation in changing the direction of innovation activities undertaken by corporate and public ventures. Therefore, it becomes critical to understand the repercussions of misconduct allegations on innocent startups.

In this study, I examine whether such episodes reverberate across the sector, affecting the outcomes of other startups developing similar technology as the alleged perpetrator. The relationship between misconduct allegations and innocent startups' performance is multifaceted. I theorize that reputational concerns of investors not only force them to reduce their investment exposure to such technologies. But these investors can also strategically use the misconduct allegations to either negotiate for a better deal or terminate perceived underperforming ventures. The combined forced and strategic dynamics can result in entrepreneurs deciding not to participate in financing rounds to protect their ventures from demanding investors. To shed light on these dynamics, data on 86 misconduct allegations against startups in the USA spanning from 1998 to 2020 were meticulously gathered. Employing a stacked difference-in-difference model, the study evaluates the impact of these allegations on innocent startups' financing opportunities. The findings reveal that startups developing similar technologies as the alleged perpetrator tend to experience reduced funding and encounter challenges in raising capital after allegations are revealed.

Interestingly, startups that are geographical proximity to the perpetrator do not experience any negative impact from misconduct allegations. Furthermore, the study uncovers the differential effects of various types of misconduct, such as technological misconduct and sexual harassment, on financing outcomes. Moreover, we find evidence supporting our reputational mechanism playing a role in propagating the negative spillover effects of misconduct allegations. While both reputable and non-reputable investors exhibit negative responses to misconduct allegations, we find that non-VCs and less experienced investors drastically reduce their exposure to innocent startups developing similar technology as the alleged perpetrators. This is indicative of investors' primary concern to protect their reputation from being stigmatized through association with innocent startups developing similar technology as the perpetrators.

In sum, it becomes apparent that navigating the aftermath of misconduct allegations requires a delicate balance for entrepreneurs and investors. Startups may need to weigh the benefits of association with a particular technology, especially during the early stage period, against the potential risks posed by such misconduct allegations.

4 Paper 3 - Role of investors' reputation in the resilience of syndication networks

Investor networks play a paramount role in bolstering the entrepreneurial ecosystem as extensively documented in the extant literature. In particular, these networks have contributed to an increase in investments, better governance mechanisms, and fostering innovation within the entrepreneurial landscape. Investor's reputation constitute the key element in the formation and survival of such networks. Much of the existing research studies have relied upon the ex-post and static context investors' reputation, proxied by successful exit or investments in certain innovative ventures, to understand its impact on the performance of future ventures. There remains a gap in understanding how these networks evolve as it navigate new opportunities or challenges over time.

In this paper, my co-author and I seek to address this gap by investigating the role of investors' reputations in influencing the syndication activity. We take advantage of the exogenous reputational shock induced by the misconduct allegations against startups like FTX, Theranos, and others to empirically observe changes in the syndication decisions and network structure. We theorize that such reputational shocks can induce co-investors to strategically appropriate better network positioning and financing deals from the tainted investors. Conversely, co-investors may completely overlook these misconduct allegations owing to over-reliance on the positive prior experience with the tainted investors. Additionally, fears of reputational costs may deter co-investors from severing ties with the tainted investor altogether.

To unravel the dynamics of investor networks in the face of reputational shocks, we curated a dataset spanning misconduct allegations against startups in the US from 1998 to 2020. We, then, employ a stacked difference-in-difference model to evaluate whether there are any changes in the syndication behavior of investors after misconduct allegations against startups.

Our findings reveal that investors tend to recalibrate their syndication strategies in response to reputational shocks, albeit without completely severing ties with the tainted investor. Instead, they choose to reduce co-investment amounts and deal sizes in syndicated deals involving the tainted investor. This strategic reduction in co-investment reflects concerns over potential reputational damage and the perceived loss in expected gains from syndication. Furthermore, the severity and nature of the misconduct allegation appear to influence investor responses, with technologically misleading claims and sexual harassment allegations inducing greater responses relative to other types of misconduct.

5 Contributions

The first paper contributes primarily to the value capture theory (Gans & Ryall ,2017; James et al. ,2013; Yilmaz, Naumovska, & Miric ,2023, and others). The appropriation capabilities of firms operating in developing economies with weak IPR regimes have been understudied. Much of the earlier studies have focussed on how firms can avoid leakages in appropriation in such economies, this paper has focussed on how firms can leverage non-market strategies - primarily tough reputation - in enhancing their capabilities in tackling trademark infringements and protecting their lucrative markets from infringers. It also sheds light on the fact that the tough reputation of a trademark holder does not confer protection in low lucrative markets. Therefore, it raises potential opportunities for strategic alliances or licensing with other competitors to ensure that the infringers do not capture value by extensively infringing in low lucrative markets. More interestingly, it also contributes to the strategic use of litigation in generating protection for even non-registered trademarks of firms with tough reputation, akin to (Fink, Fosfuri, Helmers, & Myers ,2022).

The second paper contributes to the extant literature on corporate fraud and scandals (Cumming, Dannhauser, & Johan ,2015; Efendi, Srivastava, & Swanson ,2007; Gurun, Stoffman, & Yonker ,2018). While previous work has focused on various aspects such as the characteristics of fraudulent firms, predictors of fraud, and detection mechanisms, we specifically investigate how misconduct allegations impact the performance of entrepreneurial ventures. This study reveals that misconduct allegations significantly hinder innocent startups' ability to secure investments, particularly from less experienced investors who struggle with screening and monitoring. These negative effects persist over time and encompass a wide range of misconduct allegations. Furthermore, this work contributes to the research exploring the stigmatization by association mechanism in corporate fraud (Naumovska & Zajac ,2022; Paruchuri & Misangyi ,2015). While past research has mainly highlighted stigma as the primary mechanism of the spillover effect, we shed light on investors' strategic behavior of investors to undertake terminations in the guise of misconduct allegations. Additionally, we provide evidence of heterogeneous negative effects based on the type of misconduct allegation and differentiate between investors based on their resources and prominence, revealing its influences on their investment decisions after a misconduct allegation.

The third paper contributes significantly to the understanding of the evolution of investors' networks. In particular, it provides a deeper understanding of the resilience of investors' networks despite the reputational shock induced by misconduct allegations. It appears that co-investors fear reputational loss arising from a breach of trust if they terminate ties with tainted investors. The informal mechanisms underlying such networks may play a critical role in coinvestors decision to carry on syndicating with the tainted investors despite their misjudged investments in startups perpetrating misconducts in the entrepreneurial landscape.

6 Future Avenues for Research

In this subsection, I discuss the primary future research avenues emanating from the research undertaken in this thesis. Beginning with the first paper, an interesting line of iniquiry would be to investigate the boundary conditions of the deterrence effect developed through tough reputation. To be specific, I intend to investigate whether firms employ strategies in employing their non-market factors, such as the reputation of being tough, to protect their intellectual property rights. Theeke & Lee ,2017, argue that firms can choose to initiate litigation strategies to protect their knowledge-based resources in a multi-market industry. However, it is not clear whether firms consider in which market to exhibit such rivalrous behavior. On one hand, an exhibition of rivalrous behavior by incumbents through litigation strategies can disrupt the market with competitors retaliating aggressively. This could result in incurring considerable disruption in a particular market. On the other hand, incumbents can gain considerable advantage by developing a reputation of tough litigant to deter future infringers. I intend to exploit this tension to investigate whether firms take into consideration the nature of value appropriation from a particular market (say low revenue generation market) to initiate litigation strategies yet gain the benefits of deterrence effect emanating from tough reputation manifesting across all markets.

An underexplored element in the second paper is the founders' characteristics, which can greatly influence investors' subjective judgments and investment decisions. For instance, similarities between innocent startups and perpetrators in founders' traits might serve as a transmission mechanism of negative effects on innocent startups. In contrast, a founder's reputation as a serial or successful entrepreneur can mitigate these negative effects. There is a growing debate on the impact of highly-publicized scandals, such as Theranos, on triggering biases among investors related to a founder's race, gender, or origin. It will be an important avenue for future research to investigate how such founder's characteristics can help in mitigation or propagation of the negative effects of misconduct allegations. Furthermore, it will be interesting to explore whether it generates disparity in founding and financing opportunities for entrepreneurs belonging to certain socio-economic and cultural backgrounds.

References

Agarwal, R., Ganco, M., & Ziedonis, R. H. (2009). Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. *Strategic Management Journal*, *30*(13), 1349–1374.

Arora, A., Fosfuri, A., & Gambardella, A. (2004). *Markets for technology: The economics of innovation and corporate strategy*. MIT press.

Bolton, G., Greiner, B., & Ockenfels, A. (2013). Engineering trust: reciprocity in the production of reputation information. *Management science*, *59*(2), 265–285.

Chahine, S., Filatotchev, I., Bruton, G. D., & Wright, M. (2021). "success by association": the impact of venture capital firm reputation trend on initial public offering valuations. *Journal of Management*, *47*(2), 368–398.

Chakraborty, I., & Ewens, M. (2018). Managing performance signals through delay: Evidence from venture capital. *Management Science*, *64*(6), 2875–2900.

Cumming, D., Dannhauser, R., & Johan, S. (2015). Financial market misconduct and agency conflicts: A synthesis and future directions. *Journal of Corporate Finance*, *34*, 150–168.

Dollinger, M. J., Golden, P. A., & Saxton, T. (1997). The effect of reputation on the decision to joint venture. *Strategic management journal*, *18*(2), 127–140.

Efendi, J., Srivastava, A., & Swanson, E. P. (2007). Why do corporate managers misstate financial statements? the role of option compensation and other factors. *Journal of financial economics*, *85*(3), 667–708.

Ely, J., Fudenberg, D., & Levine, D. K. (2008). When is reputation bad? *Games and Economic Behavior*, *63*(2), 498–526.

Fink, C., Fosfuri, A., Helmers, C., & Myers, A. F. (2022). Submarine trademarks. *Journal of Economics & Management Strategy*, *31*(4), 818–840.

Galasso, A., & Luo, H. (2021). Risk-mitigating technologies: The case of radiation diagnostic devices. *Management Science*, *67*(5), 3022–3040.

Galasso, A., & Luo, H. (2022). When does product liability risk chill innovation? evidence from medical implants. *American Economic Journal: Economic Policy*, *14*(2), 366–401.

Gans, J., & Ryall, M. D. (2017). Value capture theory: A strategic management review. *Strategic Management Journal*, *38*(1), 17–41.

Gulati, R. (1998). Alliances and networks. *Strategic management journal*, *19*(4), 293–317.

Gurun, U. G., Stoffman, N., & Yonker, S. E. (2018). Trust busting: The effect of fraud on investor behavior. *The Review of Financial Studies*, *31*(4), 1341–1376.

Hurwitz, M. A., & Caves, R. E. (1988). Persuasion or information? promotion and the shares of brand name and generic pharmaceuticals. *The journal of law and economics*, *31*(2), 299–320.

James, S. D., Leiblein, M. J., & Lu, S. (2013). How firms capture value from their innovations. *Journal of management*, *39*(5), 1123–1155.

Kokkodis, M., & Ipeirotis, P. G. (2016). Reputation transferability in online labor markets. *Management Science*, *62*(6), 1687–1706.

Mendonça, S., Pereira, T. S., & Godinho, M. M. (2004). Trademarks as an indicator of innovation and industrial change. *Research policy*, *33*(9), 1385–1404.

Nahata, R. (2008). Venture capital reputation and investment performance. *Journal of financial economics*, *90*(2), 127–151.

Nanda, R., & Rhodes-Kropf, M. (2017). Financing risk and innovation. *Management science*, *63*(4), 901–918.

Nasirov, S. (2020). Trademark value indicators: Evidence from the trademark protection lifecycle in the us pharmaceutical industry. *Research Policy*, *49*(4), 103929.

Naumovska, I., & Zajac, E. J. (2022). How inductive and deductive generalization shape the guilt-by-association phenomenon among firms: Theory and evidence. *Organization Science*, *33*(1), 373–392.

Paruchuri, S., & Misangyi, V. F. (2015). Investor perceptions of financial misconduct: The heterogeneous contamination of bystander firms. *Academy of Management Journal*, *58*(1), 169–194.

Rossi, M. (2024). Competition and reputation in an online marketplace: Evidence from airbnb. *Management Science*, *70*(3), 1357–1373.

Somaya, D. (2012). Patent strategy and management: An integrative review and research agenda. *Journal of management*, *38*(4), 1084–1114.

Theeke, M., & Lee, H. (2017). Multimarket contact and rivalry over knowledge-based resources. *Strategic Management Journal*, *38*(12), 2508–2531.

Yilmaz, E. D., Naumovska, I., & Miric, M. (2023). Does imitation increase or decrease demand for an original product? understanding the opposing effects of discovery and substitution. *Strategic Management Journal*, *44*(3), 639–671.

When the Gloves Come Off: Dynamics of Private Trademark Enforcement

Shreekanth Mahendiran[1], Chirantan Chatterjee[2], Anthony Dukes[3], and D. Daniel Sokol[4]

[1]HEC Lausanne

[2]Professor of Economics of Innovation and Global Health, University of Sussex Business School

[3]Professor of Marketing, Marshall School of Business, University of Southern California

[4]Professor of Law, Gould School of Law and Marshall School of Business, University of Southern California

Abstract

This research explores the role of trademark litigation in protecting a trademark against future infringement in markets where government enforcement is weak. Incumbents reputation as a tough litigant can convey to potential counterfeiters that a trademark-holding firm would sue upon entry. We explore this idea empirically in the context of pharmaceutical trademarks in India using the framework of a stylized theoretical model. We construct a database of trademarks and examine litigation activity by certain trademark holders. Our findings indicate that litigation reduces subsequent infringement. Because litigation can be extremely costly for a trademark-holding firm, it is worthwhile only when it has legal advantages in pursuing cases. Not all trademark-holding firms have such legal advantages and are, therefore, better off surrendering to infringers and incurring a cycle of settlements with future infringement.

Keywords : Trademarks, Reputation, Litigation, Intellectual Property Rights

1 Introduction

At the origin of most brands is the trademark[1] itself (Friedman ,1985). Because the trademark serves as an identifier of the brand (Meyers-Levy ,1989), firms are understandably concerned about competitors using names that lead the consumer to mistake another product for its own. Governments in many countries enable firms to protect their brand names as intellectual property in the form of trademarks. The registration of a trademark confers upon its holder the exclusive right to its use.[2] To enforce this right, government institutions, including courts, establish clear and effective boundaries for trademark infringement. The threat or actual use of private party litigation can serve as a credible deterrent against blatant infringement (Cohen ,1986). For example, in North America or the E.U., a firm, whose trademarked brand is violated, can rely on the courts to consistently interpret claims of infringement through private lawsuits. However, in emerging economies, like those of India and Pakistan, government enforcement and judicial institutions remain poorly equipped to reliably protect trademarks and other forms of intellectual property (IP) (Fink, Maskus, & Qian ,2016).[3] Without reliable protection against trademark infringement, firms that develop legitimate trademarks in such markets face threats to their marketing investments. This research examines how firms protect their trademarks in regimes with weak legal enforcement.

Entry of imitators, or infringers, can result in a discovery (advertisement) or substitution resulting in an increase or decrease, respectively, in value capture by the incumbents (Qian ,2014a, 2014b; Yilmaz, Naumovska, & Miric ,2023. However, such value appropriation potential is subject to boundary conditions such as upstream technology production, downstream product market, and intellectual property regime in a particular country. To begin with, high technology-intensive industries, such as pharmaceuticals, focus heavily on leveraging patents in determining the appropriability strategies to capture value in the market (James, Leiblein, & Lu ,2013). In these industries, there is a dearth of understanding about trademarks as a complementary asset in appropriating value (Castaldi ,2020; Mendonça, Pereira, & Godinho ,2004). Second, the downstream commercialized products are of a credence nature heightening the importance of quality signaling through trademarks to build trust and brand loyalty among consumers (Hurwitz & Caves ,1988; Nasirov ,2020; Tenn & Wendling ,2014). In our setting, the presence of infringers or imitators can result in value destruction and welfare-reduction for trademark holders

[1]Note that we use other terms ”trademark” and ”brand name” interchangeably.

[2]To protect its exclusive rights granted by trademark, the firm must show that its trademarks are unique and/or that consumers identify the mark with the trademark-owner (e.g., through advertising and other methods of promotion).

[3]See also the International Anti-Counterfeiting Coalition Submission to the 2020 Special 301 Report of the United States Trade Representative. `https://www.regulations.gov/document?D=USTR-2019-0023-0042` [Accessed April 20, 2022].

and consumers, respectively, rather than complementary or substitution effect theorized under the extant literature (Yilmaz et al. ,2023).

Finally, much of the research on trademark infringement has focused on developed markets like the U.S. (e.g., Ertekin, Sorescu, & Houston ,2018). In these markets, the standards for evidence of infringement are well-defined in the courts and where legal recourse is generally reliable. Similar reliability may not be present in weaker legal regimes, however. Given these unique circumstances, the decision to protect a trademark through litigation in developing countries involves substantially different considerations than considered in the prior literature that focuses on more developed legal regimes for IP.

To study this, we situate our study in the pharmaceutical sector in India. Even though pharmaceutical firms can register the names of their branded drugs as trademarks with the Government of India (GoI), they are routinely subject to infringement by infringers. Consider, for instance, the trademark Exodep, a branded drug introduced by Sun Pharmaceutical Industries Limited (a domestic Indian generic medicine manufacturer) in the therapeutic market for central nervous system drugs. Eight copycat drugs were eventually introduced by rival entrants with names such as “Esdep”, “Odep”, and “Exidep” to compete against Sun’s Exodep. Such copycats threaten a legitimate brand’s ability to recoup its investment in reputation building (Grossman and Shapiro 1988). Further, they confuse consumers and hinder their access to high-quality products on the market (Commuri ,2009; Gao, Lim, & Tang ,2017). For pharmaceutical products in particular, such confusion can lead to serious health consequences for consumers. Consequently, the World Health Organization has recognized counterfeit medicines as “one of the urgent health challenges for the next decade”.[4]

Our empirical analysis uses nearly 100,000 monthly observations of pharmaceutical trademarks in India from 2007 to 2013. The data consist of 2,062 brand names in 96 markets (defined by drugs sharing the same active molecule). For each brand, we observe its trademark registration status, its time duration in the market, and its market performance. We then augment these observations with details about trademark litigation pursued by firms that own trademarks. In order to assess the degree of trademark infringement, we constructed a distance metric between a trademark and any subsequent trademark launched by competitors: the minimum number of edits, letter changes, from one name to the other. For instance, to go from “Exitol” to “Oxetol” requires only two edits. Using this metric, we compute two measures of trademark infringement. For any trademarked brand name, we define (i) the average (name) distance of all subsequent trademark, and (ii) the volume of infringement (number of subsequent brand names in the same therapeutic market with a distance of two or fewer) in the same therapeutic market.

[4]Refer to https://www.who.int/news-room/photo-story/photo-story-detail/urgent-health-challenges-for-the-next-decade

These two measures give us a two-dimensional assessment of the level of infringement for a given trademark. We then evaluate the impact of litigation by regressing the level of infringement on the amount of litigation activity by the trademark-holding firm.

Our first set of results focuses on the conditions in which infringement is likely to arise. We find no evidence that the registration of a trademark provides effective protection. Specifically, trademark registration in India does not seem to have a meaningful deterrent effect on infringement. In fact, there are as many or more infringers associated with registered trademarks than with unregistered brand names. These empirical regularities establish that marketers in India cannot rely on a strong regime of IP protection like those in developed markets, such as North America or the E.U. With this condition established, our second set of results focuses on the impact of the litigation as an entry deterrent for future infringers. Our empirical analysis indicates that a firm that litigates on behalf of its trademark subsequently experiences both a reduction in the number of infringers and an increase in the average distance in its competitors' names from its own name.

As revealed by our theoretical framework, the litigation-deterrent mechanism requires several moderators. First, deterring infringement requires the litigating firm to be judicially efficient, which we proxy by the amount of litigation experience. Consequently, not all firms find it optimal to establish a reputation for toughness through litigation. Some firms must surrender to the infringer by cutting a settlement deal with the current infringer and living with the prospect of future infringement. Second, we find that the litigation-deterrent mechanism is more visible in lucrative markets. Given the high cost of litigating, only certain markets are worth defending. Further consistent with this, we find that litigating firms are earn more revenue than non-litigating ones. This finding does not imply that litigation causes the firm to be more profitable but rather suggests that tough firms pursue litigation because they have potentially more to gain from defending their market than weak firms.

This study contributes to three strands of literature. First, we add to the value capture theory by bringing to the fore the role of tough reputation in protecting trademarks, a complementary asset, in the face of infringement by infringers (Gans & Ryall ,2017; Jacobides, Knudsen, & Augier ,2006; James et al. ,2013; Yilmaz et al. ,2023. Second, extant literature is scarce regarding how firms can protect its IPR in a weak regime. The research has focussed on MNE firms incentives to undertake investment in innovative activities (Lamin & Ramos ,2016), informational disclosure by registering their IPR (Keupp, Friesike, & Von Zedtwitz ,2012, leakages in tacit knowledge through research collaboration (Belderbos, Park, & Carree ,2021), and changes in market dynamics to external shocks (Adbi, Chatterjee, & Mishra ,2022) in a weak IPR regime. Our focus, however, is how domestic firms can protect their IPR from infringement in a weak IPR regime. Our empirical analysis reveals that firms undertaking aggressive enforcement through judicial courts confer deterrence from the infringement activity. However, firms operating in such regimes may have to consider implementing market strategies, in addition to strategic licensing, to fend off infringers in low lucrative markets.

Finally, following a long tradition of research from pharmaceutical economics, Hurwitz & Caves ,1988 points out the relevance of signaling quality in pharmaceuticals because of concerns over safety and effectiveness. Our work, by contrast, highlights the use of litigation as a reputation mechanism when traditional forms of money-burning, such as national brand advertising (Kirmani & Rao ,2000), are not feasible as is the case for specialized medicines. And, in the context of Indian pharmaceuticals, Bennett & Yin ,2019), show how marketing channels play a role in the availability and prices of high-quality drugs in the market, particularly when government enforcement against infringement is inadequate. By examining litigation in the pharmaceutical context, we establish how and when the law can be an important non-market tool for firms in developing economies.

The paper proceeds as follows: Section 2 provides the theoretical framework identifying the conditions for infringement and its subsequent deterrence through tough reputation, Section 3 details the sample construction, primary dependent and independent variables, Section 4 establishes the empirical approach to test the hypotheses, Section 5 presents the estimation results offering evidence on the impact of tough reputation, proxied by litigation experience, on the measures of infringement, and finally we conclude in Section 6.

2 Theory and Hypotheses Development

In this section, we develop the theory that hinges upon the reputation models, such as Kreps & Wilson ,1982, yet stylized to our litigation setting to identify conditions directly applicable to our empirical setting. Specifically, we theorize the interactions of a trademark-holding firm with a series of potential infringing firms to generate hypotheses that can be empirically tested with the data. These hypotheses provide the antecedent conditions of infringement and the litigation-deterrence equilibrium in which tough firms thwart trademark infringement but weak ones do not.

Firms undertake strategic considerations about investments in their research and development (R&D hereon) efforts to develop novel technologies and their subsequent commercialization with downstream products to extract economic rewards in the market (Arora, Fosfuri, & Gambardella ,2004; Baldwin, Hienerth, & Von Hippel ,2006; Gunther McGrath & Nerkar ,2004; Somaya ,2012, and others). For instance, Agarwal, Ganco, & Ziedonis ,2009, theorize a tough reputation mechanism wherein firms undertake patent litigations to limit the labor mobility of employee inventors thereby retaining critical knowledge in the organization and reducing the prospects of value capture by competitors. Equally important, Block, Fisch, Hahn, & Sandner ,2015; Castaldi ,2020; Kaiser, Cuntz, & Peukert ,2023; Nasirov ,2020, and others, have extensively documented the strategic importance of trademarks in the commercialization of novel and incremental innovation, in addition to products with underlying patent-expired or non-patentable technologies.

This particular role of trademarks becomes critical in industries, such as pharmaceuticals, characterized by high technological intensiveness, product differentiation, and the presence of intermediaries (Mendonça et al. ,2004; Nasirov ,2020). To explain, firms undertake considerable investments in identifying novel drugs or repurposing older drugs to new markets. However, firms rely upon intermediaries such as doctors and pharmacists to prescribe their downstream products to final consumers. The market is also highly competitive, especially with the possibility of entry from generic manufacturers, inducing firms to undertake product differentiation strategies to distinguish themselves from the competition (Tenn & Wendling ,2014). Furthermore, firms use trademarks to signal their quality thereby developing trust about the product among the intermediaries and final consumers (Hurwitz & Caves ,1988). Finally, a trademarking strategy can serve as an associative mechanism influencing the prescription behavior of intermediaries and consumption by final consumers (Fickweiler, Fickweiler, & Urbach ,2017). This guarantees continued revenue generation for a firm through drug production under the same trademark or entering into strategic licensing agreements with competitors even beyond patent expiry. Therefore, protecting investments in innovation through trademarks is important for marketers (Cohen ,1986; Krasnikov, Mishra, & Orozco ,2009) as well as for the efficient function of a market economy (Landes & Posner ,1987).

Given its significance, and relative ease of imitation, infringers undertake infringement to appropriate the economic returns of an incumbent's trademark. As with other intellectual property rights, registration of a trademark with governmental institutions does not confer protection against infringement. It depends upon the intellectual property regime in a particular country and the incentives for a firm to actively enforce its IPR by accessing monitoring and judicial avenues (Cremers, Gaessler, Harhoff, Helmers, & Lefouili ,2016). A strong IPR regime provides clear and defined rewards and sanctions for innovative and infringement activities, respectively (Huang, Geng, & Wang ,2017). In such regimes (e.g., the US or the EU), a trademark holder relies on consistent interpretations in court so that litigation is relatively less costly. Consequently, it reduces the prospect of a firm experiencing a severe infringement of its trademark by an infringer.[5] On the other hand, a trademark holder faces uncertainty over the enforcement of their rights, especially concerning the judicial outcomes, in a weak IPR regime. Consequently, a trademark holder will experience relatively higher incidences of severe infringement by infringers (Belderbos et al. ,2021).

Under a weak IPR regime, an infringer's expectation about the type of trademark holder, arbitration cost, and value capture influences their decision to infringe a particular trademark. An infringer will evaluate whether the trademark holder is tough or weak against any infringement activity. Here, the trademark holder can be disincentivized to enforce its IPR through legal institutions as it faces higher costs of litigation, lengthy duration of court procedures, and uncertainty over the legal outcome. Infringers, then, are more likely to expect the trademark holder to be of the weak kind who either relies upon informal institutions to enforce its IPR or consider coexisting strategy with them (Belderbos et al. ,2021).

Qian ,2014a, 2014b, provide evidence on market strategies, such as separating or pooling equilibrium, that trademark-holders can initiate to protect their market. A separating equilibrium transpires into setting a higher price to signal higher quality to consumers but still permits the infringers to exist in the market. This works in the setting of luxury goods as the trademark-holder not only separates itself from the infringer by setting a higher price, thereby generating higher revenue but also from the advertisement effect generated by the infringing product. Alternatively, trademark-holders could decide to be in a pooling equilibrium where the objective is to reduce the market share captured by the infringer, thereby deterring their entry into the market (Tenn & Wendling ,2014). However, an infringer could still find revenue-maximization opportunities in a pooling equilibrium and continue to undertake infringement upon the trademark holder. Therefore, there exists value capture potential for infringers to undertake infringement under a weak IPR regime.

Building upon this, we explore the conditions that facilitate infringement in the market. These conditions constitute the registration status of a trademark, the lucrativeness of the trademark, and market. An infringer will prefer to enter a market with a moderate number of competing products so that they can strategically blend with other competitors in the market. This increases the search cost of trademark holders to identify trademark infringement and implement subsequent enforcement activities. This guarantees infringers enough time to capture the economic returns through infringement and exit the market, if necessary when the incumbent approaches to cease the infringing activity.

[5] We define (a) *severe infringement* as those incidences where the competitor trademark is very similar to the incumbent's registered trademark; (b) *modest infringement* as those ambiguous cases where the competitor's trademark is similar but does include elements of visual and oral presentation that distinguish it from the incumbent's registered trademark; and (c) *no infringement* as those incidences where the competitor's trademark is dissimilar to the incumbent's trademark.

Within this product market, infringers have to incur search costs to identify the trademark that holds the potential for high economic return in the short run. Registration of a trademark by an incumbent signals the inherent product value to competitors and potential infringers (Belderbos et al. ,2021; Ethiraj & Zhu ,2008). Incumbents consider the tradeoff between signaling the value of downstream commercialized products to competitors, through trademark registration, and the cost of protecting it from future infringement. For instance: Fink, Fosfuri, Helmers, & Myers ,2022, shows that firms even implement the strategic practice of ”submarine trademarks” to avoid information disclosure about potential market entry and value of a product to competitors. Firms will register their trademark to develop trust and brand loyalty among the intermediaries and consumers once the product is determined to be economically valuable. Infringers, then, can reduce their search cost by targeting the registered trademarks, especially given the expected poor enforcement and penalization under the weak IPR regime. Therefore, we have the following hypothesis:

Hypothesis 1: Registration of a trademark does not deter infringement.

Next, an infringer's incentive is to maximize revenue by infringing upon the incumbent's trademark in the short run. A lucrative market will generally constitute products with relatively higher prices providing sufficient conditions for an infringer to appropriate economic value. Second, infringers can target market segments untapped by the trademark holder to undertake infringement (Adbi et al. ,2022). The enforcement costs for an incumbent trademark holder might be high in such market segments, thereby creating the condition for infringement. Second, infringers can appropriate the reputation and trust of the incumbent's trademark by catering to consumers with unmet demand. Therefore, it is more likely that infringers will target the lucrative markets to undertake infringement.[6] The above arguments give us the following hypothesis:

Hypothesis 2: Infringement occurs in relatively lucrative markets.

Trademark holders will expect a relatively higher occurrence of infringement, ranging from modest to severe, and incur higher costs to protect their trademarks under a weak IPR regime. Our earlier arguments reveal that the market-based deterrence strategies would not completely deter the infringers from entering the market and subsequently undertake infringement upon an incumbent's trademark. Then, there are three costly choices for a trademark holder namely (a) litigation, (b) settlement, and (c) coexist in the face of infringement (Crampes & Langinier ,2002). The settlement and co-existence options might be considered an economically viable strategy, as the presence of infringers can generate an advertisement effect and enhance the future revenue of the incumbent (Qian ,2014b). The loss in current

[6] Similarly, the lucrativeness of the trademark can attract more infringement in the market (Howard, Bach, Berndt, & Conti ,2015).

market share can be considered a tradeoff to effective monitoring costs that have to be incurred by the trademark holder. However, there are severe reputational costs for trademark holders in pharmaceutical industries. Infringers are expected to produce lower-quality products that may not meet the necessary safety standards for consumption by consumers. Any adverse events caused by the infringer can result in the trademark holder bearing negative reputational consequences. Such adverse events can shift away the trademark holder's demand to other branded products in the market (Hermosilla & Ching ,2024), and alter the direction of innovation activities undertaken by the trademark holder (Galasso & Luo ,2021, 2022). Finally, Ertekin et al. ,2018, uses an event study with time series data to understand the financial consequences of trademark litigation. The results suggest that litigation by a trademark-holding firm warns investors about an infringement threat in the short term but builds their confidence in the trademark in the long term.

A trademark holder's decision to surrender the market to one infringer can lead to repeated infringement in the future. For instance: Intas's trademark, Gabapin, was registered in India in 1997. In 2001, another trademark, Gabatin, was introduced by Neon Laboratories in the same therapeutic market as Gabapin. Intas opted not to file a legal case against Neon for trademark infringement. Subsequently, a third firm, Macleods Pharmaceuticals introduced its product with the trademark "Gabamin" in 2006, thereby infringing on both Intas' and Neon's brands.

An incumbent's tradeoff for litigating extends beyond simply considering legal costs versus market share losses to the infringer. Unlike settlements, litigation is typically very public and conveys to potential infringers the consequences of infringement. Preventing future infringement requires that potential infringers feel threatened by the incumbent. Our mechanism assumes heterogeneity in a firm's willingness to pursue litigation, thereby transforming into a credible threat for possible infringers operating under a weak IPR regime. Thus, an incumbent's effort to build such a reputation signals their underlying motivation and capability dynamics to undertake costly litigation against potential infringers, indicating their willingness to protect their rights (Onoz & Giachetti ,2023). If the incumbent is effective in signaling their willingness to be a tough litigant, then it can refuse to settle and punish the infringing firm by preventing it from recouping entry costs. In sum, an incumbent's decision to incur costly litigation in courts and build a tough reputation can stop the cycle of settlements by keeping future infringers from entering the market.

The incumbent's litigations against the infringement activity will raise the costs for the infringers, thereby driving out any economic return enjoyed through infringement. Furthermore, such a tough reputation will disincentive potential infringers to undertake infringement against the trademark holder.

Instead, the infringer will shift their infringement activity to those trademark-holders who do not pursue any litigation or enter markets where the tough trademark holder is not present. Therefore, we have the following hypothesis:

Hypothesis 3: Tough reputation, proxied by litigation experience, implies measures of lower infringement.

Corollary to Hypothesis 2, the incumbent's tough reputation can be considered an effective deterrence strategy only if it lowers infringement in lucrative markets. The costly litigations against infringements are justifiable to incumbents as they offer protection of their trademarks in the lucrative markets. If not, then incumbents will not pursue any investment efforts to build a tough reputation against trademark infringement as it does not translate into a credible threat for the infringers. This is possible under the scenario where the infringer is certain that any litigation action will not result in an unfavorable outcome, such as an injunction, forcing it to cease the infringement activity. Infringers, thus, can continue to extract positive economic returns through infringement activity. This is unlikely as both the trademark holder and infringer will face similar uncertainty over the court's interpretation of infringement. Therefore, there exists the litigation-deterrence condition, even under a weak IPR regime, wherein the tough reputation of incumbents will necessarily result in greater deterrence of infringers in the lucrative markets. This gives us the following hypothesis.

Hypothesis 4: The deterrent effect of tough reputation is more visible in lucrative markets.

Concluding, these four hypotheses tell us how the above theoretical mechanism can manifest in our data. The first two refer to the antecedent conditions of our mechanism, while the latter two refer to the deterrence outcomes.

3 Methods

3.1 Sample Construction

In this sub-section, we discuss the steps undertaken to construct the sample as illustrated in Appendix Figure A1. The empirical analysis is situated in the Indian pharmaceutical sector. The Indian context facilitates investigating the role of litigation in trademark protection under a weak intellectual property regime. As it has been documented, intellectual property rights, including trademarks, held by pharmaceutical firms may not be well-enforced by the Government of India (GoI) (Fink ,2004) - an assumption that we establish empirically later. This allows us to test whether the deterrence effect of litigation triumphs over any pecuniary advantage gained through trademark infringement by competitors under a weak IPR regime. The pharmaceutical sector context enables us, operationally, to identify incidences of trademark infringement as the products and medicine markets are formally categorized by their anatomical therapeutic classification (EphMRA) (Benischke & Bhaskarabhatla ,2022; Grabowski & Vernon ,1992).

We source information from three datasets to build the sample. These datasets include (a) Manupatra India Law Legal (MILL hereon) for legal documents on trademark infringement, (b) All India Organization of Chemists and Druggists (AIOCD hereon) for economic variables such as price, quantity sold, and others of pharmaceutical products in the Indian market, and (c) Registrar of Trademarks, Government of India, (RoT hereon) for information on trademark registration status.

In the first step, we manually searched the MILL database with three keywords namely, trademark, trademark litigation, and trademark infringement to source trademark-related litigations in India. We identified 76 unique trademark infringement litigations in the pharmaceutical sector. From these legal documents, we extracted specific details such as (a) infringed and infringing trademark, (b) infringed and infringing firm[7], (c) duration, and (d) outcome, in the event a verdict had been passed.[8] In the second step, we use the extracted information, especially the trademark and firm, to map to the AIOCD database. This database constitutes market-related variables and varies at the firm, anatomical therapeutic chemical classification (EphMRA - at different levels), trademark, and month level between April 2007 and October 2013. Through this process, we identified four trademarks namely Oxetol, Veinz, Susten, and Niftran with infringement litigations for which the market-related variables were available in the AIOCD database. We use the therapeutic market (EphMRA 2) and molecule details of these four legally contested trademarks to extract the entire set of pharmaceutical products and construct the dataset for empirical analysis. For instance, the molecules of the infringed and infringing trademark in the case of Oxetol were oxcarbazepine and lactitol, respectively. These molecules belonged to the therapeutic market comprising anti-epileptics and anti-depressant drugs. Thus, we extracted the entire set of pharmaceutical products sold in the therapeutic market of anti-epileptics and anti-depressants market.[9] Finally, we sourced information about the registration status of each product by accessing the website of the Controller General of Patents, Designs, and Trademarks, Office of the Registrar of Trademarks, Gov-

[7]They are addressed as plaintiff and defendant, respectively, in the legal documents.

[8]We also extracted details about the judge and court in which the litigation was pursued by the plaintiff (infringed firm).

[9]The sample structure is such that it begins with firms that manufacture drugs in five therapeutic markets (EphMRA2 categories) represented by the codes N03, N06, G03, G04, and V06. These therapeutic markets sell drugs related to anti-epileptics, anti-depressants, urological/erectile, urinary, and sweeteners, respectively. Each therapeutic market contains several four-digit EphMRA categories representing molecule/product markets. The therapeutic market, N03 anti-epileptics, contains 23 four-digit EphMRA categories. Under each four-digit EphMRA category, a firm can produce and sell drugs with one or more trademarks. For example, Sun Pharmaceutical Industries Limited sells drugs under two trademarks - Lonazep and Maxgalin - in the four-digit EphMRA category, N03A03 (molecule name: Clonazepam) and N03A18 (molecule name: Pregabalin), respectively.

ernment of India. This assisted in the classification of registered trademarks and non-registered brand names, in addition to accurately identifying cases of trademark infringement.[10]

The final dataset used for the analysis comprised 325 firms operating in five therapeutic markets (namely N3, N6, G3, G4, and V6) under which there were 96 different molecules and 2,062 trademarks from April 2007 to October 2013. Of these 325 firms, Intas Pharmaceuticals and Sun Pharmaceuticals had the greatest number of trademarks, 97 and 74 respectively, in these markets. In sum, we use an unbalanced dataset that varies by the firm (f), therapeutic market (g), molecule (m), trademark[11] (b). and month (t), with 98,888 observations for the analysis.

3.2 Dependent Variables

Trademark infringement is defined as the "*unauthorized use of a trademark or service mark on or in connection with goods and/or services in a manner that is likely to cause confusion, deception, or mistake about the source of the goods and/or services*".[12] It relies upon the notion of similarity between two trademarks used by an incumbent and competitor to sell pharmaceutical products in the same therapeutic market (EphMRA 2 level). We capture the similarity with the function *minEdit*(b, b') that calculates the minimum number of edits of a subsequent competing trademark b' required to arrive at an incumbent's trademark b in the same therapeutic market. For instance, consider Oxetol as the incumbent trademark and Exitol as the competing drug name which applied for trademark registration at a later period. We can ascertain that Exitol requires two letters to be edited to arrive at the incumbent's trademark Oxetol. It is important to note that b' denotes subsequent competing trademarks meaning that it encompasses those trademarks where the competitor had never applied for trademark registration or applied after the incumbent's registration. For instance, let us take the case of Oxetol which had 482 competing trademarks in the same market. Only 428 (89%) either never registered a trademark or did so after Oxetol's trademark application. Therefore, we considered these 428 as competing trademarks to construct the measures of trademark infringement.

Building upon this, we construct two measures of infringement as the dependent variable namely (a) the distance of competing trademarks and (b) the number of infringing trademarks. The former captures the intensity of infringement, at an intensive margin, whereas the latter captures the volume of infringement, at an extensive margin, faced by a firm. These two measures give us a two-dimensional

[10] It was decided to retain trademarks with the application information as it facilitated distinguishing infringing from infringed trademarks. This resulted in the exclusion of about 3% of the observations owing to a lack of information about the trademark application.

[11] Note that we use the term trademark and brand name interchangeably in this paper.

[12] Refer to the definition by USPTO - https://www.uspto.gov/page/about-trademark-infringement

assessment of the level of infringement for a given trademark

Distance of competing trademarks: This variable aims to capture the intensity of infringement faced by each trademark held by an incumbent. To explain, an incumbent's trademark can be considered as experiencing a higher intensity of infringement if eight out of ten subsequent competing trademarks are similar. On the other hand, it can be considered as experiencing a lower intensity of infringement if two out of ten subsequent competing trademarks are similar. We operationalize this by averaging the distances of competing trademarks b' in the same therapeutic market as the incumbent trademark b. A higher average, in essence, signifies that an incumbent's trademark experiences a lower threat to its core market and vice-versa. We compute the intensity of infringement for an incumbent's trademark b in market g during a particular period t as follows:

$$\text{Avg Dist TM}_{f,g,b,t} = \frac{\sum_{b' \neq b} \text{minedit}(b,b')}{\#\{b' \in g \text{ in month } t \mid b' \neq b\}}$$

Number of infringing trademarks: This variable captures the extent to which competing trademarks infringe an incumbent's trademark. A brief analysis of the litigation documents revealed that the distance between an infringed and infringing trademark can be characterized with minEdit$(b, b') \leq 2$. Thus, we compute the number of infringing trademarks faced by an incumbent trademark b in therapeutic market g during a particular period t as follows:

$$\text{Infringing TM}_{f,g,b,t} \equiv \#\{b' \in g, \text{ in month } t \mid b' \neq b \text{ and minEdit}(b, b') \leq 2\}$$

While it narrowed down similar trademarks, some competing trademarks did not qualify as infringing because they were not deceptively similar to the incumbent's. For instance, consider an incumbent trademark Oxetol with the competing trademarks Acetol and Exitol. The minimum number of edits to arrive at Oxetol from either Acetol or Exitol is 2. However, the phonetics and visual representation are more similar between Oxetol and Exitol relative to Oxetol and Acetol. Therefore, Acetol cannot be considered as infringing upon Oxetol. Given this, we employ the above equation to identify all competing trademarks similar to an incumbent's trademark, followed by manual checks to ensure that only those demonstrating deceptive similarity, and potentially cause confusion, are considered as an infringing trademark.

3.3 Independent Variables

Litigation experience of a firm: This is the primary variable of interest as the study examines whether a tough reputation, proxied by litigation experience, of a firm deters subsequent trademark infringement by competitors. We define the reputation of toughness as a function of the willingness of a firm to litigate against infringers. This definition relies upon the correspondence that a higher number of past litigations against trademark infringement of a firm indicating a greater willingness to litigate against infringement in the future, therefore developing a tough reputation against trademark infringement. Given this, we identified firms that litigated as plaintiffs in a trademark infringement case between 2007 and 2013 using the MILL database - similar to Agarwal et al. ,2009. The data constituted 19 firms that had filed one litigation case, six firms that had filed two, three firms that filed three to five cases, and one firm that had filed eight cases.[13]

Dummy for registered trademarks: We generate a dummy variable indicated with one for registered trademarks and zero otherwise. There were 969 registered trademarks, about 47% of total trademarks, present in the sample. This allows us to examine whether trademark registration offers any deterrence from infringement by a competitor.

Dummy for lucrative trademarks: A lucrative trademark faces a higher risk of infringement because of its higher economic potential. Consequently, incumbents will be inclined to pursue litigation as a deterrence strategy when it protects their lucrative trademark against infringers. To investigate this, we define lucrative trademarks as those commanding significant market share within a specific molecule submarket. The measure relies upon the relative positioning of a trademark within each molecule submarket. We first calculate each trademark's market share by dividing its revenue by the total revenue generated within a specific molecule submarket for each period t. We take the median of each trademark's market share over time, denoted by *TM Market Share*$_{f,g,m,b}$, to capture its time-invariant position in a molecule submarket. Finally, we classify a trademark as lucrative if its market share is greater than the median market share within a specific molecule submarket; otherwise, it is deemed as non-lucrative. We formally represent this with the following equation:

$$\text{Lucrative TM}_{f,g,m,b} = \begin{cases} 1 & \text{if TM Market Share}_{f,g,m,b} > \text{Median TM Market Share}_{g,m} \\ 0 & \text{if TM Market Share}_{f,g,m,b} \leq \text{Median TM Market Share}_{g,m} \end{cases}$$

Dummy for lucrative molecule submarkets: An infringer's decision to enter a market, and infringe a trademark within it, can be motivated by the lucrativeness of a market. An incumbent will pursue litigation strategies if they deter infringers from entering lucrative markets. We consider the lucrativeness

[13]The total number of unique litigation cases summed up to 51 between the period of 1987 to 2012. Out of these 51 litigations, 44 occurred within a five-year range (before/after) of the sample (beginning in 2007). Five out of the seven litigations that did not occur within this five-year overlap consisted of firms that had filed only one litigation. In essence, most of the sample represents firms with relevant litigation experience in their immediate past; therefore, they are suitable for studying the impact of litigation experience on deterring future counterfeiters.

of a market at the level of molecule submarket.[14] We define lucrative molecule submarkets as those commanding significant market share within a specific therapeutic market. To operationalize this, we calculate each molecule's market share by dividing its revenue by the total revenue generated within a specific therapeutic market g for each period t. We take the median of each molecule's market share over time, denoted by *Sub Market Share*$_{g,m}$, to capture its time-invariant position in a therapeutic market. We classify a molecule submarket as lucrative if its market share is greater than the median market share across molecule submarkets within a specific therapeutic market; otherwise, it is deemed as non-lucrative. We formally represent this with the following equation:

$$\text{Lucrative Molecule Sub Market}_{g,m} = \begin{cases} 1 & \text{if Sub Market Share}_{g,m} > \text{Median Sub Market Share}_g \\ 0 & \text{if Sub Market Share}_{g,m} \leq \text{Median Sub Market Share}_g \end{cases}$$

3.4 Control Variables

Defense experience of a firm: A firm's experience as a defendant in trademark infringement cases can be considered a sign of its toughness. In addition, it can be a good source of legal knowledge strengthening its capability to manage litigations. We include this as a control variable as it may influence a firm's decision to litigate against trademark infringement. We treat this variable as continuous similar to the treatment of litigation experience of a firm.

MRP Distance: This variable captures the relative pricing of a trademark therefore its position in a particular market. A high relative price signals higher product quality inducing potential infringers to exploit such perceptions, free-ride on the trademark, and capture its economic potential (Qian ,2014b). We use the relative measure of market-to-retail price, denoted as MRP Dist$_{f,g,m,b,t}$, derived by taking the distance of trademark b MRP relative to the average MRP for all trademarks in a particular molecule submarket, m, at time t.

$$\text{MRP Dist}_{f,g,m,b,t} = \frac{1}{\#\{b' \in m\}} [\textstyle\sum_{b \in m} (MRP_{f,g,m,b',t} - MRP_{f,g,m,b,t})]$$

With this derivation, a negative value of MRP Dist$_{f,g,m,b,t}$ implies that a trademark MRP is larger than the average price of pharmaceutical products sold within a molecule submarket m at time t.

Firm age: We include firm age to control for fewer resource acquisition challenges (Gulati ,1998), strong external networks (Chen, Mehra, Tasselli, & Borgatti ,2022), and legitimacy (Rao ,1994). A potential infringer may perceive an older firm as established with access to greater resources and strong

[14] We classify the lucrativeness at the trademark and molecule submarket level, even though the trademark infringement is identified within a therapeutic market. We undertake this to capture the nuanced decision-making of infringers to target a lucrative molecule submarket or trademark to infringe and capture the economic rents. This does not rule out the possibility that infringers may decide to enter and target a market based on the lucrativeness of a therapeutic market.

networks, including legal, influencing their decision to approach the courts against infringement. Therefore, this may induce a potential infringer to choose not to infringe upon trademarks of pharmaceutical products belonging to older firms, relative to younger firms in the industry.

4 Empirical approach

4.1 Estimating the conditions of trademark infringement

We explore whether the registration and lucrative characteristics are correlated with trademark infringement in the market. Our Hypothesis 1 indicates that registration would not necessarily guarantee deterrence from infringement and might induce competitors to infringe upon a trademark. In addition, the economic potential of a lucrative trademark and market will increase the likelihood of trademark infringement (Hypothesis 2). We consider the following regression specification to test our hypotheses formally:

$$Y_{f,g,b,t} = \alpha + \gamma_1 TMREG_{f,g,m,b,t} + \gamma_2 LTM_{f,g,m,b} + \gamma_3 LMM_{g,m} + \Delta\mathbf{X} + \delta\text{FE} + \epsilon_{f,g,m,b,t} - -Eq1$$

We use least square dummy variable (LSDV hereon) and negative binomial regression (NBREG hereon) models to estimate the above equation with the dependent variable: trademark distance and the logarithm of number of infringing trademarks, respectively. On the right-hand side, the coefficient γ_1 captures the relationship between registration status (denoted as TM REG) and trademark infringement. Similarly, the coefficients γ_2 and γ_3 capture whether the lucrativeness of trademark and molecule submarket, denoted as LTM and LMM respectively, attracts more infringement or not. The $\mathbf{X}$ constitute the vector of control variables: number of patents, MRP distance, and firm age. The FE constitutes the vector of fixed effects at the therapeutic market, firm, and time (month) level. We cluster the standard errors at the firm level to account for the possible dependence of observations within a firm.

4.2 Estimating the impact of tough reputation on trademark infringement

We expect a firm's tough reputation, proxied by litigation experience, to deter future trademark infringement, and most importantly, that this deterrence effect will be strongest in a lucrative market (Hypothesis 3 and 4). We estimate the following regression specification to test our hypotheses:

$$Y_{f,g,b,t} = \alpha + \beta_1 TMREG_{f,g,m,b,t} + \beta_2 LTM_{f,g,m,b} + \beta_3 LMM_{g,m} + \beta_4 LitExp_{f,t} + \beta_5 LitExp_{f,t} * TMREG_{f,g,m,b,t} + \beta_6 LitExp_{f,t} * LTM_{f,g,m,b} + \beta_7 LitExp_{f,t} * LMM_{g,m} + \Delta\mathbf{X} + \delta\text{FE} + \epsilon_{f,g,m,b,t} - -Eq2$$

Equation 2 is the same as Equation 1 with the addition of litigation experience (denoted as Lit Exp) and its interaction with registration status, the lucrativeness of trademark and market, with the same dependent variables, control variables, and fixed effects. The primary coefficients of interest are: β_4, β_5, β_6, and β_7. The coefficient β_4 captures the partial effect of litigation experience whereas the main effect of litigation experience is derived by taking a weighted average of β_4, β_5, β_6, and β_7 (Cornelißen & Sonderhof ,2009). The coefficient β_5 captures the heterogeneity in the deterrence effect of litigation experience by trademark registration status on our measures of trademark infringement. Similarly, β_6 and β_7 capture the heterogeneity in the deterrence effect of litigation experience by the lucrativeness of trademark and molecule submarket, respectively. The $\mathbf{X}$ constitute the vector of control variables: number of patents, defense experience of a firm, MRP distance, and firm age. The FE constitutes the vector of fixed effects at the therapeutic market, firm, and time (month) level. We report the firm-level clustered standard errors from our regression estimations.

Challenges could be raised to any causal interpretation of litigation experience owing to endogeneity concerns, potentially emanating from omitted variable bias, in the specified model - Equation 2. We address this concern by implementing an instrumental variable estimation strategy to derive a consistent estimator of our four primary variables of interest: litigation experience and its interaction with registration status, lucrativeness of trademark and molecule submarket. We construct a set of instruments based on the timing of Abbreviated New Drug Application (ANDA hereon) approvals by US Food and Drug Administration (US FDA). To explain, a successful approval will exogenously change the incentive for firms to develop a tough reputation against trademark infringement. First, more generally, firms have to worry about the prospect of reputational loss because of any negative events triggered by an infringing trademark in the market. Naumovska & Zajac ,2022; Paruchuri & Misangyi ,2015, and others provide evidence of the transmission of stigma effect from perpetrators to other innocent firms within the same industry. Importantly, stakeholders will likely impose severe stigma penalties for any negative incidents emerging from trademark infringement, as incumbents endeavor to develop their reputation and quality through their trademarks (Barlow, Verhaal, & Hoskins ,2018). This increases the prospect of heightened regulatory oversight and the risk of withdrawal of ANDA approval by US FDA to protect its consumers from purchasing susceptible products sold by the infringers in the market. Incumbents especially those with successful ANDA approvals will face higher risks and costs as infringers continue to infringe upon their trademarks. Consequently, it will alter their incentives to litigate against infringers in the Indian market to retain their access to the US market.

Another important element to note is that the exogenous variation is derived from the timing of approval of ANDA application by US FDA.[15] Previous research has noted that the timing of approval is variable, at least from the perspective of these prospective firms, as there is considerable year-on-year variation (Reiffen & Ward ,2005). The timing of ANDA approvals meets the exclusion restriction as it can only influence the infringer's decision through the incumbent's litigation efforts. In other words, it would not directly influence the infringer's decision to infringe incumbents' trademarks. Given this, we sourced information on ANDA approvals for the period between January 1982 to February 2021 from the Orange Book available on the US FDA website. We use this to construct a set of variables based on the ANDA approvals received by each firm during a particular month. Our instrument variables are: (a) number of ANDA approvals received, (b) cumulative total of ANDA, (c) square terms of (a) and (b), (d) interaction of (a) and (b) with registration status, lucrativeness of brand, and molecule submarket.

5 Results

5.1 Sample description

[Insert Table 1]

As mentioned in section 3.1, we have 325 pharmaceutical firms selling 2,062 trademarks across 96 molecules and five therapeutic markets between April 2007 and October 2013. We observe substantial variability in the number of trademarks held by firms to market their products. Approximately 71 percent of the 325 firms have five or fewer trademarks, followed by 25 percent selling six to 29 trademarks, and 4 percent selling 30 or more trademarks in the market. While only 47 percent of the 2,062 trademarks were registered (refer to Table 1), we observed that firms with more trademarks are more inclined to register their trademarks with the GoI. On average, firms with five or fewer trademarks register 33 percent of their trademarks whereas those with 30 or more trademarks register about 60 percent of them. Additionally, we noted that high-lucrative trademarks tend to have higher registration rates than low-lucrative trademarks (58 percent versus 40 percent respectively). Such a difference in registration is not observed based on the lucrative nature of the molecule submarket since about 47 percent of trademarks are registered in both low and high-lucrative molecule submarkets.

Regarding litigation activity, it is notable that only 29 firms have opted to pursue legal action against trademark infringement. Among these, 19 firms filed at least one litigation, followed by seven with two

[15] A prospective firm can submit an ANDA application for molecules whose patent had expired or challenge the validity of an existing patent. This requires the firm to incur costs to demonstrate the bio-equivalence of their products and invest efforts to handle the legal procedure to achieve a successful application. Once the application is submitted, the process is based on the internal capacity of US FDA to review and approve/reject the application.

to three litigations each, and three firms that initiated a maximum of eight litigations against trademark infringement. The low quantum of litigation by infringed firms supports the assumption that potential infringers and other market participants, such as consumers, may perceive the average firm in the market as the weak kind. It is important to note that the data does not reveal any systematic difference between firms that initiated litigation against trademark infringement and those that did not. For instance, Sun Pharmaceuticals Industries Limited, with 74 trademarks in the market, filed the highest litigations at eight against infringers. Interestingly, Intas Pharmaceuticals Limited, which had the highest number of trademarks (97) in the market, did not initiate any litigation against trademark infringement. Rather it only defended itself against such cases or went into settlement with its competitors.[16]

Moving on to the dependent variables, the data reveals a negative correlation (-0.242) between the measures of trademark distance and number of infringing trademarks, suggesting that they capture similar yet not identical dimensions of trademark infringement. From Table 1, the average distance between the registered trademark and subsequent trademarks belonging to a competitor is marginally lower relative to those non-registered (7.97 versus 7.54). Additionally, it is worth noting that the risk of being infringed for registered trademarks is nearly twice that for non-registered trademarks (0.24 versus 0.13 respectively). A similar ratio of infringement is observed when we compare low and high-lucrative trademarks despite a short distance between low (or high) lucrative and competing trademarks.[17] Therefore, the descriptive statistics indicate that trademark registration is not a strong deterrent against infringement. Furthermore, the lucrativeness of a trademark and market is positively associated with the nature of trademark infringement experienced by the incumbents in the market.

5.2 Factors of Infringement: Trademark Registration and Market Lucrativeness

[Insert Table 2]

Table 2 provides the marginal effects of factors of infringement derived from estimating Equation 1. These results show that registered trademarks are associated with greater infringement than non-registered trademarks. From Column 1, the coefficient for registered trademarks, relative to non-registered, is negative and statistically significant for the distance of competing trademarks. The coefficient (b = -0.5362, se = 0.0645) means that non-registered trademarks have three more different letters to be edited relative to registered trademarks to arrive at an incumbent's trademark. In simpler terms,

[16] 21 firms were defendants in one trademark infringement case, followed by two firms and one firm defending against two and three trademark infringement cases, respectively, in the sample.

[17] We find a similar pattern for trademark distance and level of infringement in terms of the lucrativeness of the molecule submarket.

when an incumbent has a registered trademark, its competitors tend to name their trademarks much more similarly to it, relative to those that are not registered. This is also substantiated by almost twice the relative risk of infringement (b = 1.7472, se = 0.2620) experienced by registered trademarks (Column 2).

Furthermore, the intersection of registration status and lucrativeness of trademark/market accentuates infringement by competitors. First, we observe that competing trademarks are more similar and infringe at a greater level for highly lucrative registered trademarks than low lucrative trademarks. In contrast, highly lucrative non-registered trademarks face a higher risk of infringement, although they do not face a significant intensity of infringement from competing trademarks. As we compare the coefficients between these two interaction variables, even qualitatively, it becomes evident that highly lucrative registered trademarks face much greater intensity and risk of infringement from competitors, in comparison to non-registered trademarks. A similar picture emerges as we examine the coefficients for registered trademarks in the lucrative molecule submarket and non-registered trademarks in the lucrative molecule submarket.

Overall, the analysis indicates that registration does not protect a trademark from infringement. Registered trademarks appear to attract more competing products with similar trademarks relative to non-registered and low-lucrative trademarks. In addition, the more lucrative a trademark is, the more likely a competitor is to infringe. The lucrativeness of a molecule submarket does not appear to be associated with any substantial change in the intensity and extent of a trademark infringement. The results remain qualitatively similar when we examined firms with legal exposure being a plaintiff (litigation experience) or defendant (defense experience) in trademark infringement cases. In sum, these findings provide support to hypotheses 1 and 2.

5.3 Impact of Tough Reputation on Intensity of Infringement

[Insert Table 3]

We examine the impact of a firm's tough reputation, proxied by litigation experience, on the intensity of infringement faced by each trademark. In Table 3, Column M1 presents the regression results from the LSDV model without any fixed effects. Column M2 estimates the same model with the firm, therapeutic market, and time (in months) fixed effects with clustered standard errors at the firm level. Columns M3 and M4 report the regression estimates from the instrumental variable approach with IV-2SLS and IV-GMM estimators, respectively. Column 5 reports the regression estimates with time-varying firm and therapeutic market fixed effects, in addition to time (in months) fixed effects, with clustered standard errors at the firm level.

We assess the relevance of the instruments and whether the primary variables of interest are endogenous. The Kleibergen-Paap rk Wald F statistic is greater than the critical values (F = 20.447) and Hansen J Statistic (p-value = 0.2624) indicating that the instruments are relevant in explaining the variation in litigations pursued by the firms. Furthermore, the endogeneity test fails to reject the null hypothesis meaning that the instrumented variables are exogenous. This is evident as the estimated coefficients of the primary variables of interest from the LSDV and IV-2SLS/IV-GMM are qualitatively similar. Given this, we rely upon the estimated coefficients to make a causal interpretation of the impact of litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket on the distance of competing trademarks.

[Insert Figure 1]

Figure 1 depicts the main and interaction effects of litigation experience on the distance of competing trademarks (refer to Appendix Table A2 for the estimated marginal effects). The Y-axis represents the change in distance of competing trademarks for firms that had pursued litigations relative to those that had not pursued any litigations against trademark infringement. For instance, when the X-axis value is two and the Y-axis is 0.1262 (se = 0.0350) in Panel A, it suggests that competitors tend to differentiate their trademark with one different letter, on average, for firms with two litigation experience relative to those with zero litigation against trademark infringement. Panel A demonstrates that the distance between a trademark and its competing trademarks increases for firms with more litigations against trademark infringement. Competitors name their trademarks much differently when comparing firms with eight litigations versus those with two litigations. This translates to a change in the magnitude of four versus one different letter from the focal trademark. In sum, this supports hypothesis 3 that trademark infringement by competitors is deterred, as evidenced by the reduction in the intensity of infringement, as a firm develops a tough reputation by undertaking litigations against trademark infringement.

The estimated marginal effects of the interaction terms reveal a heterogeneous effect of litigation experience on the distance of competing trademarks. Beginning with registration status (Panel B in Figure 1), the impact of litigation experience for non-registered trademarks is economically and statistically significant on the infringement intensity. Among registered trademarks, we find a greater reduction in the intensity of infringement is experienced by firms that have undertaken more litigations against trademark infringement. The observed difference in magnitude does not translate to a statistically significant difference between firms with one and eight litigation experience (b = 0.0255 versus 0.2042, respectively, see Column 3 in Appendix Table A2). Furthermore, the divergence in deterrence effect between non-registered and registered trademarks increases significantly as a firm develops a tougher reputation against trademark infringement. Competitors differentiate their trademarks approximately four times more for non-registered trademarks of firms with litigation experience, on average, than their registered trademarks. In sum, we conclude that building a tough reputation induces competitors to name their trademarks more distantly for registered and non-registered trademarks, where the deterrence effect is stronger for the latter.

Regarding trademark lucrativeness, the economic and statistical significance of litigation experience for low-lucrative and high-lucrative trademarks becomes stronger as a firm initiates more than one litigation against trademark infringement. We find that the divergence in the deterrence effect of a tough reputation for low-lucrative and high-lucrative trademarks increases considerably as the firm develops a tougher reputation (see Panel C in Figure 1). The effect is stronger for low-lucrative than high-lucrative trademarks. For instance, competitors will differentiate their trademarks with two letters, at least, relative to a low-lucrative trademark as the focal firm undertakes three or more litigations. The same magnitude of deterrence is true for high-lucrative trademarks for firms that have undertaken seven or more litigations.

Moving on, the effect of litigation experience is statistically significant for low and high-lucrative molecule submarkets. Similar to trademark lucrativeness, the divergence in the deterrence effect between low and high-lucrative molecule submarket increases as firms pursue more litigation against trademark infringement. But, most importantly, the effect is stronger for high lucrative, almost twice, than low lucrative molecule submarket (see Panel D in Figure 1). Competitors, thus, differentiate their trademarks in high-lucrative molecule submarkets considerably as a firm develops a tough reputation. Overall, the upward trend of litigation experience suggests that competitors are deterred from trademark infringement in lucrative markets as a firm develops a tough reputation. The interaction effects of litigation experience with trademark and molecule submarket lucrativeness provide evidence that this deterrence effect is more pronounced in lucrative markets, thus supporting hypothesis 4.

5.4 Impact of Tough Reputation on Risk of Infringement

[Insert Table 4]

We examine the impact of a firm's tough reputation on the risk of infringement faced by each trademark. In Table 4, Column M1 presents estimates from the NBREG model without any fixed effects. Column M2 presents estimates of the same model with the firm, therapeutic market, and time (in months) fixed effects with clustered standard errors at the firm level. Column M3 presents estimates from the instrumental variable regression with control function approach. Column 4 reports the regression estimates incorporate time-varying firm and therapeutic market fixed effects, in addition to time (in months) fixed effects, with standard errors clustered at the firm level.

We follow the steps outlined in Wooldridge ,2010, to estimate the instrumental variable regression with control function approach. First, we estimate the residuals from the first stage regressions with litigation experience, its interaction with registration status, lucrativeness of brand and molecule submarket as the dependent variables. The independent variables constitute the set of instruments namely – (a) number of ANDA approvals, (b) cumulative total of ANDA approval, (c) interaction term of (a) with registration status, lucrativeness of brand, and molecule submarket. The estimated residuals of these endogenous variables are then plugged into the second-stage regressions. From Column 3 in Table 4, it is observed that none of these residual terms are statistically significant, indicating no endogeneity problem. Therefore, we rely upon the estimated coefficients from the negative binominal model reported in Column 2 of Table 4 to make causal interpretations of litigation experience on the risk of infringement faced by a trademark.

[Insert Figure 2]

Figure 2 illustrates the main and interaction effects of litigation experience on the number of infringing trademarks (refer to Appendix Table A3 for the estimated marginal effects). The Y-axis denotes the change in the risk of infringement for a trademark held by firms that had pursued litigations relative to those that did not pursue any litigation against trademark infringement. For instance, in Panel A, when the X-axis value is two and the Y-axis is 1.0100 (se = 0.0514), it suggests that the risk of infringement for a focal trademark increases by 1 percentage point, on average, for firms with two litigation experience compared to those with zero litigation. Panel A shows that there is no statistically significant change in the risk of infringement as a firm establishes a tougher reputation. A similar picture emerges when examining the interaction effect of litigation experience and registration status on the risk of infringement (refer to Panel B).

However, the impact of litigation experience varies significantly for low and high-lucrative molecule submarkets. We find that a trademark in high-lucrative molecule submarkets experiences a lower risk of infringement as a firm develops a tougher reputation by undertaking litigations. For instance, there is a reduction in risk of infringement by four percentage points for firms with one litigation relative to those with zero litigation. The risk of infringement decreases substantially as a firm undertakes more litigations; with almost a 28 percentage point reduction in risk of infringement for firms with eight litigations relative to those with zero litigation.

In contrast, we observe the opposite trend for trademarks in low-lucrative molecule submarkets. The risk of infringement faced by a trademark in low-lucrative molecule submarkets increases as a firm develops a tougher reputation. For instance, the risk of infringement from being the same for a firm with one and zero litigation increases considerably to 42 percentage points as the firm pursues at least eight litigations against trademark infringement. This evidence, when juxtaposed with that of the high-lucrative molecule submarkets, suggests a reorganization of infringers in the market. Infringers may shift their activity from high-lucrative molecule submarkets to low-lucrative molecule submarkets due to an incumbent's decision to build a tougher reputation.

Additionally, an examination of Panel B and Panel C reveals no change in the risk of infringement for registered/non-registered and high-lucrative trademarks. It is the low-lucrative trademarks whose risk of infringement increases by 25 percentage points as an incumbent develops a tougher reputation against trademark infringement. Given this, we conjecture that the majority of the shift in infringement activity from high to low-lucrative molecule submarkets, as a consequence of an incumbent's tougher reputation, is directed towards low-lucrative trademarks. In conclusion, an incumbent's tougher reputation, through litigations against trademark infringement, results in a more pronounced deterrence effect in lucrative markets, supporting hypothesis 4.

5.5 Robustness Tests

We performed a set of robustness checks to confirm the reliability of the impact of litigation experience on the measures of trademark infringement. These checks involved altering the nature of the primary independent variables and boundary conditions, such as considering only molecules without patent expiry. We made the following changes to the primary estimation model, as specified in Equation 1 and 2: (a) lagged form of litigation experience (see Appendix Table A4 and A10), (b) accounting for patent expiry (see Appendix Table A5 and A11), (c) subsample of registered trademarks (see Appendix Table A6 and A12), and (d) categorical form of litigation experience (see Appendix table A7 and A14).

It is important to note that the regression with a subsample of molecules without patent expiry was conducted to assess whether the firm's decision to litigate against trademark infringement was influenced by the need to protect their market due to patent expiration (Reitzig ,2004).[18] Another important

[18]We sourced patent information, such as applicant name and approval date for molecules, in the dataset from Derwent Innovation. We found that there were four molecules for which patents administered by the US (2), India (0), and WIPO (2) were expiring during the period of analysis. It should be noted that there were no additional molecules for which patents were expiring when the period from 2005 to 2015 was considered. Therefore, we constructed a subsample by excluding these four molecules for which patents were expiring during the period of analysis and re-estimated the regressions.

robustness check is the treatment of litigation experience as a categorical variable, instead of continuous, which allows us to better account for the fact that each litigation experience brings unique lessons to all parties of a trial, which may not accrue continuously or linearly. A review of the trial details indicates several sporadic factors that arise in different cases. Such factors include the nature of the litigation claims (trademark infringement or passing-off litigation), the specific types of evidence employed, and the duration of the legal battle. In addition, each litigation unfolds uniquely, from a trademark infringement case to a trademark infringement and passing-off case, with variations in the actions taken by the infringed/infringing firm and in the legal relief sought. Thus, the categorical treatment was to capture the non-linearity of the impact of a tougher reputation by comparing firms with different levels of litigation experience and those with none. Overall, these robustness checks are consistent with the primary results and support hypotheses 3 and 4.

5.6 Relative Profitability

[Insert Table 5]

Finally, we evaluate whether litigating firms (tough kinds) are more profitable than non-litigating firms (Hypothesis 5). Assuming small relative marginal costs for medicines, we assess the claim on profitability of firm types by comparing their mean annual revenue (in real US $) between litigating and non-litigating firms in Table 5. Non-litigating firms earned almost US $0.5 million (se = 37,681), whereas litigating firms earned over US $ 1.7 million (se = 248,142). The difference of US $ 1.2 million is statistically significant at the 1 % level. Overall, tough trademark holders are generally more profitable than weak ones. We hasten to qualify that this does not establish that, by litigating, any firm can be more profitable than by not litigating. Rather, we argue that the success of litigation reflects a relatively higher incentive to litigate for tough trademark holders.

6 Conclusions

This paper has explored how firms can build a tough reputation, by pursing litigations against infringement, to defend a trademark's market in legal regimes where IPR enforcement is spotty. We first establish that, in countries like India, trademark registration may not be fully effective at thwarting blatant imitation of trademarks. Without clear guidelines for courts to uphold trademarks, firms are on their own to defend their markets. Thus, only firms with better access to courts or are otherwise more adept at litigating have a shot at preventing infringement of their brand names. In particular, we delineate differential use of the courts as the “single-crossing” property through which it is possible to establish a tough reputation through litigation. This theoretical delineation of litigation “toughness” forms the basis for our empirical strategy using the Indian pharmaceutical industry. It further permits us to proxy toughness by observing which firms choose to litigate.

To measure the level of infringement, we constructed a trademark similarity metric between incumbents and other competitors. By regressing the volume of trademark litigation by an incumbent on future infringement, we find that litigation tends to reduce the number of subsequent infringers and the degree to which competitors choose imitating names. As such, we empirically establish a reputation mechanism through which litigation acts. Prior work on trademark litigation has focused on regimes such as the E.U. and the U.S. and only focused on incidental stock market behavior (Ertekin et al. ,2018). Our current findings provide a conceptual basis for that prior work as well as guide firms on whether litigation is a useful non-market strategy tool in developing market regimes.

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References

Adbi, A., Chatterjee, C., & Mishra, A. (2022). How do mnes and domestic firms respond locally to a global demand shock? evidence from a pandemic. *Management Science*, *68*(12), 9003–9025.

Agarwal, R., Ganco, M., & Ziedonis, R. H. (2009). Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. *Strategic Management Journal*, *30*(13), 1349–1374.

Arora, A., Fosfuri, A., & Gambardella, A. (2004). *Markets for technology: The economics of innovation and corporate strategy*. MIT press.

Baldwin, C., Hienerth, C., & Von Hippel, E. (2006). How user innovations become commercial products: A theoretical investigation and case study. *Research policy*, *35*(9), 1291–1313.

Barlow, M. A., Verhaal, J. C., & Hoskins, J. D. (2018). Guilty by association: Product-level category stigma and audience expectations in the us craft beer industry. *Journal of Management*, *44*(7), 2934–2960.

Belderbos, R., Park, J., & Carree, M. (2021). Do r&d investments in weak ipr countries destroy market value? the role of internal linkages. *Strategic Management Journal*, *42*(8), 1401–1431.

Benischke, M. H., & Bhaskarabhatla, A. (2022). Negative incentives and regulatory capture: Noncompliance with price ceilings on essential medicines in india. *Journal of Management Studies*.

Bennett, D., & Yin, W. (2019). The market for high-quality medicine: retail chain entry and drug quality in india. *Review of Economics and Statistics*, *101*(1), 76–90.

Block, J. H., Fisch, C. O., Hahn, A., & Sandner, P. G. (2015). Why do smes file trademarks? insights from firms in innovative industries. *Research Policy*, *44*(10), 1915–1930.

Castaldi, C. (2020). All the great things you can do with trademark data: Taking stock and looking ahead. *Strategic Organization*, *18*(3), 472–484.

Ceccagnoli, M., & Jiang, L. (2013). The cost of integrating external technologies: Supply and demand drivers of value creation in the markets for technology. *Strategic Management Journal*, *34*(4), 404–425.

Chen, H., Mehra, A., Tasselli, S., & Borgatti, S. P. (2022). Network dynamics and organizations: A review and research agenda. *Journal of Management*, *48*(6), 1602–1660.

Cohen, D. (1986). Trademark strategy. *Journal of Marketing*, *50*(1), 61–74.

Commuri, S. (2009). The impact of counterfeiting on genuine-item consumers' brand relationships. *Journal of marketing*, *73*(3), 86–98.

Cornelißen, T., & Sonderhof, K. (2009). Partial effects in probit and logit models with a triple dummy-variable interaction term. *The Stata Journal*, *9*(4), 571–583.

Crampes, C., & Langinier, C. (2002). Litigation and settlement in patent infringement cases. *RAND Journal of Economics*, 258–274.

Cremers, K., Gaessler, F., Harhoff, D., Helmers, C., & Lefouili, Y. (2016). Invalid but infringed? an analysis of the bifurcated patent litigation system. *Journal of Economic Behavior & Organization*, *131*, 218–242.

Ertekin, L., Sorescu, A., & Houston, M. B. (2018). Hands off my brand! the financial consequences of protecting brands through trademark infringement lawsuits. *Journal of Marketing*, *82*(5), 45–65.

Ethiraj, S. K., & Zhu, D. H. (2008). Performance effects of imitative entry. *Strategic management journal*, *29*(8), 797–817.

Fickweiler, F., Fickweiler, W., & Urbach, E. (2017). Interactions between physicians and the pharmaceutical industry generally and sales representatives specifically and their association with physicians' attitudes and prescribing habits: a systematic review. *BMJ open*, *7*(9), e016408.

Fink, C. (2004). *Intellectual property and the wto*. World Bank.

Fink, C., Fosfuri, A., Helmers, C., & Myers, A. F. (2022). Submarine trademarks. *Journal of Economics & Management Strategy*, *31*(4), 818–840.

Fink, C., Maskus, K. E., & Qian, Y. (2016). The economic effects of counterfeiting and piracy: A review and implications for developing countries. *The World Bank Research Observer*, *31*(1), 1–28.

Friedman, M. (1985). The changing language of a consumer society: Brand name usage in popular american novels in the postwar era. *Journal of Consumer Research*, *11*(4), 927–938.
Galasso, A., & Luo, H. (2021). Risk-mitigating technologies: The case of radiation diagnostic devices. *Management Science*, *67*(5), 3022–3040.
Galasso, A., & Luo, H. (2022). When does product liability risk chill innovation? evidence from medical implants. *American Economic Journal: Economic Policy*, *14*(2), 366–401.
Gans, J., & Ryall, M. D. (2017). Value capture theory: A strategic management review. *Strategic Management Journal*, *38*(1), 17–41.
Gao, S. Y., Lim, W. S., & Tang, C. S. (2017). Entry of copycats of luxury brands. *Marketing Science*, *36*(2), 272–289.
Grabowski, H. G., & Vernon, J. M. (1992). Brand loyalty, entry, and price competition in pharmaceuticals after the 1984 drug act. *The journal of law and economics*, *35*(2), 331–350.
Gulati, R. (1998). Alliances and networks. *Strategic management journal*, *19*(4), 293–317.
Gunther McGrath, R., & Nerkar, A. (2004). Real options reasoning and a new look at the r&d investment strategies of pharmaceutical firms. *Strategic Management Journal*, *25*(1), 1–21.
Hermosilla, M., & Ching, A. T. (2024). Does bad medical news reduce preferences for generic drugs? *Journal of Marketing*, *88*(1), 160–178.
Howard, D. H., Bach, P. B., Berndt, E. R., & Conti, R. M. (2015). Pricing in the market for anticancer drugs. *Journal of Economic Perspectives*, *29*(1), 139–162.
Huang, K. G.-L., Geng, X., & Wang, H. (2017). Institutional regime shift in intellectual property rights and innovation strategies of firms in china. *Organization Science*, *28*(2), 355–377.
Hurwitz, M. A., & Caves, R. E. (1988). Persuasion or information? promotion and the shares of brand name and generic pharmaceuticals. *The journal of law and economics*, *31*(2), 299–320.
Jacobides, M. G., Knudsen, T., & Augier, M. (2006). Benefiting from innovation: Value creation, value appropriation and the role of industry architectures. *Research policy*, *35*(8), 1200–1221.
James, S. D., Leiblein, M. J., & Lu, S. (2013). How firms capture value from their innovations. *Journal of management*, *39*(5), 1123–1155.
Kaiser, F., Cuntz, A., & Peukert, C. (2023). Batman forever? the role of trademarks for reuse in the us comics industry. *Research Policy*, *52*(8), 104820.
Keupp, M. M., Friesike, S., & Von Zedtwitz, M. (2012). How do foreign firms patent in emerging economies with weak appropriability regimes? archetypes and motives. *Research Policy*, *41*(8), 1422–1439.
Kirmani, A., & Rao, A. R. (2000). No pain, no gain: A critical review of the literature on signaling unobservable product quality. *Journal of marketing*, *64*(2), 66–79.
Krasnikov, A., Mishra, S., & Orozco, D. (2009). Evaluating the financial impact of branding using trademarks: A framework and empirical evidence. *Journal of Marketing*, *73*(6), 154–166.
Kreps, D. M., & Wilson, R. (1982). Reputation and imperfect information. *Journal of economic theory*, *27*(2), 253–279.
Lamin, A., & Ramos, M. A. (2016). R&d investment dynamics in agglomerations under weak appropriability regimes: Evidence from indian r&d labs. *Strategic management journal*, *37*(3), 604–621.
Landes, W. M., & Posner, R. A. (1987). Trademark law: an economic perspective. *The Journal of Law and Economics*, *30*(2), 265–309.
Mendonça, S., Pereira, T. S., & Godinho, M. M. (2004). Trademarks as an indicator of innovation and industrial change. *Research policy*, *33*(9), 1385–1404.
Meyers-Levy, J. (1989). The influence of a brand name's association set size and word frequency on brand memory. *Journal of Consumer Research*, *16*(2), 197–207.
Nasirov, S. (2020). Trademark value indicators: Evidence from the trademark protection lifecycle in the us pharmaceutical industry. *Research Policy*, *49*(4), 103929.
Naumovska, I., & Zajac, E. J. (2022). How inductive and deductive generalization shape the guilt-by-association phenomenon among firms: Theory and evidence. *Organization Science*, *33*(1), 373–392.

Onoz, E., & Giachetti, C. (2023). Will rivals enter or wait outside when faced with litigation risk? patent litigation in complex product industries and international market entry. *Strategic Organization*, *21*(2), 339–379.

Paruchuri, S., & Misangyi, V. F. (2015). Investor perceptions of financial misconduct: The heterogeneous contamination of bystander firms. *Academy of Management Journal*, *58*(1), 169–194.

Qian, Y. (2014a). Brand management and strategies against counterfeits. *Journal of Economics & Management Strategy*, *23*(2), 317–343.

Qian, Y. (2014b). Counterfeiters: Foes or friends? how counterfeits affect sales by product quality tier. *Management Science*, *60*(10), 2381–2400.

Rao, H. (1994). The social construction of reputation: Certification contests, legitimation, and the survival of organizations in the american automobile industry: 1895–1912. *Strategic management journal*, *15*(S1), 29–44.

Reiffen, D., & Ward, M. R. (2005). Generic drug industry dynamics. *Review of Economics and statistics*, *87*(1), 37–49.

Reitzig, M. (2004). Strategic management of intellectual property. *MIT Sloan Management Review*.

Roberts, P. W. (1999). Product innovation, product–market competition and persistent profitability in the us pharmaceutical industry. *Strategic management journal*, *20*(7), 655–670.

Sandner, P. G., & Block, J. (2011). The market value of r&d, patents, and trademarks. *Research Policy*, *40*(7), 969–985.

Somaya, D. (2012). Patent strategy and management: An integrative review and research agenda. *Journal of management*, *38*(4), 1084–1114.

Tenn, S., & Wendling, B. W. (2014). Entry threats and pricing in the generic drug industry. *Review of Economics and Statistics*, *96*(2), 214–228.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Yilmaz, E. D., Naumovska, I., & Miric, M. (2023). Does imitation increase or decrease demand for an original product? understanding the opposing effects of discovery and substitution. *Strategic Management Journal*, *44*(3), 639–671.

8 Tables

Table 1: Summary statistics

Selected Variables	Full Sample	By registration status		By trademark lucrativeness		By molecule submarket lucrativeness	
		Not registered	Registered	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trademark distance							
Overall	7.77	7.97	7.54	7.79	7.74	7.66	7.88
	(1.25)	(1.40)	(1.01)	(1.25)	(1.25)	(1.20)	(1.29)
For firms that did not litigate	7.77	7.94	7.55	7.76	7.77	7.65	7.88
against trademark infringement	(1.25)	(1.40)	(1.01)	(1.22)	(1.30)	(1.20)	(1.29)
For firms that litigate against	7.77	8.13	7.50	7.97	7.61	7.68	7.89
trademark infringement	(1.23)	(1.41)	(0.98)	(1.40)	(1.04)	(1.16)	(1.30)
No. of infringing trademarks							
Overall	0.18	0.13	0.24	0.14	0.25	0.20	0.16
	(0.52)	(0.46)	(0.57)	(0.42)	(0.64)	(0.52)	(0.52)
For firms that did not litigate	0.18	0.12	0.25	0.14	0.25	0.20	0.16
against trademark infringement	(0.53)	(0.47)	(0.59)	(0.42)	(0.68)	(0.52)	(0.54)
For firms that litigate against	0.18	0.15	0.21	0.14	0.22	0.22	0.14
trademark infringement	(0.46)	(0.42)	(0.48)	(0.42)	(0.48)	(0.50)	(0.39)
MRP distance	-0.73	0.00	-1.54	5.07	-10.21	-1.37	-0.05
	(86.90)	(83.86)	(90.22)	(73.97)	(104.03)	(87.54)	(86.27)
Firm age (in years)	22	-	-	-	-	-	-
	(17)	-	-	-	-	-	-
Number of trademarks	2,062	1,093	969	1,277	785	1,056	1,006
% Registered	47	0	100	40	58	47	47

Notes: The table provides the mean and standard deviation (in parentheses) of trademark distance, number of infringing trademarks, MRP distance, and firm age (in years). We compute the mean of trademark distance, number of infringing trademarks, and MRP distance by taking the average across both trademarks and months between April 2007 and October 2013. The category "overall" under our dependent variables represents the entire sample; whereas, the other two categories report the descriptive statistics of our dependent variables for firms that do not undertake any litigation and those that have pursued at least one litigation against trademark infringement.

Table 2: Trademark registration and its lucrativeness are correlated with higher trademark infringement by competitors

Selected Independent Variables	Distance of Competing Trademarks	Relative risk ratio: Number of Infringing trademarks
	(1)	(2)
Registered trademark (relative to non-registered)	-0.5362***	1.7472***
	(0.0645)	(0.2620)
High lucrative trademark (relative to low-lucrative trademark)	-0.0817	1.7129***
	(0.0703)	(0.2837)
High lucrative molecule submarket (relative to low lucrative molecule submarket)	0.2188***	0.9174***
	(0.0678)	(0.1239)
Not registered and high-lucrative trademark (relative to low-lucrative trademark)	-0.0015	1.6558***
	(0.1057)	(0.4016)
Registered and high-lucrative trademark (relative to low-lucrative trademark)	-0.1621**	1.7470***
	(0.0667)	(0.3046)
Not registered and high-lucrative molecule submarket (relative to low-lucrative molecule submarket)	0.3231***	0.8175***
	(0.0928)	(0.1728)
Registered and high-lucrative molecule submarket (relative to low-lucrative molecule submarket)	0.1143**	0.9789***
	(0.0798)	(0.1601)
Other Control Variables	Number of Patents, MRP distance and Firm age (in months)	
Fixed Effects		
Therapeutic market	Yes	Yes
Month	Yes	Yes
Firm	Yes	Yes
Observations	97,622	97,622
R-square	0.2827	-
Log-Likelihood	-	-49,115
Standard Errors	Clustered at Firm level	

Notes: The table reports the marginal effects of registration status, lucractiveness of trademark, and molecule submarket on the measures of trademark infringement. This is derived from estimating the model specified in Equation 1 under section 4.1. The estimated coefficients from the regression are provided under Columns 3 and 6 for the models with the dependent variables namely distance of competing trademarks and number of infringing trademarks, respectively, in Appendix Table A1. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table 3: Effect of litigation experience on distance of competing trademarks

Selected Independent Variables	M1 LSDV	M2 LSDV	M3 IV 2SLS	M4 IV GMM	M5 LSDV
	(1)	(2)	(3)	(4)	(5)
Litigation Experience	0.1410***	0.1177***	0.1256***	0.1487***	0.0987***
	(0.0421)	(0.0344)	(0.0452)	(0.0356)	(0.0344)
Litigation Experience * Dummy for Registered Trademark	-0.0802**	-0.0751***	-0.1104***	-0.1227***	-0.0720***
	(0.0316)	(0.0270)	(0.0339)	(0.0309)	(0.0277)
Litigation Experience * Dummy for Lucrative Trademark	-0.0868*	-0.0646	-0.0615	-0.0828**	-0.0683
	(0.0499)	(0.0445)	(0.0566)	(0.0394)	(0.0451)
Litigation Experience * Dummy for Lucrative Molecule Submarket	0.0373**	0.0304	0.0561	0.0784***	0.0301
	(0.0165)	(0.0214)	(0.0422)	(0.0297)	(0.0216)
Dummy for Registered Trademark	-0.4604***	-0.5335***	-0.5208***	-0.5502***	-0.5552***
	(0.0667)	(0.0652)	(0.0629)	(0.0596)	(0.0659)
Dummy for Lucrative Trademark	0.0921	-0.0222	-0.0235	-0.0398	-0.0206
	(0.0648)	(0.0737)	(0.0761)	(0.0689)	(0.0731)
Dummy for Lucrative Molecule Submarket	0.2376***	0.1738***	0.1642**	0.1238**	0.1724**
	(0.0664)	(0.0694)	(0.0679)	(0.0630)	(0.0708)
Constant	7.6420***	7.8446***			7.8502***
	(0.0698)	(0.0560)			(0.0571)
Other Control Variables	Number of Patents, Defense Experience and its interaction with Registration Status, LTM, and LMM, MRP distance, and Firm age (in months)				
Tests for IV Regression					
Endogenity Test [Chi Square P Value]			*0.5216*		
Weak Identification Test [Kleibregen-Paap rk Wald F Statistic]			*20.447*		
Over Identification Test [Hansen J Statistic P-Value]			*0.2624*		
Fixed Effects					
Therapeutic Market	No	Yes	Yes	Yes	No
Month	No	Yes	Yes	Yes	Yes
Firm	No	Yes	Yes	Yes	No
Therapeutic Market * Year	No	No	No	No	Yes
Firm * Year	No	No	No	No	Yes
Observations	97,622	97,622	97,622	97,622	97,577
R-square	0.065	0.280	0.068	0.066	0.298
Standard Errors	Clustered at Firm level				

Notes: The table reports the estimated coefficients of primary independent variables – namely litigation experience and its interaction with registration status, the lucrativeness of trademark, and molecule submarket – with distance of competing trademarks as the dependent variable. Column 2 reports the estimated coefficients of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 5 reports the estimated coefficients of the model with year-varying firm and therapeutic market fixed effects. Column 3 and 4 report the estimated coefficients from the instrumental variable approach with 2SLS and GMM, respectively. We implemented an instrumental variable approach to resolve endogeneity concerns regarding our primary variables of interest – litigation and its interactions. The endogenous variables are litigation experience and its interaction with registration status, the lucrativeness of trademark, and molecule submarket. The instruments constitute (a) the number of ANDA approvals, (b) the cumulative total of ANDA approvals, (c) the square term of (a) and (b), (d) interactions of (a) and (b) with registration status, lucrativeness of trademark and molecule submarket. The endogeneity test fails to reject the null hypothesis that the instrumented variables are exogenous (p-value = 0.5216). Given this, we rely upon the estimated coefficients from Column 2 to infer the effect of litigation experience on the distance of competing trademarks. Reg status, LTM, and LMM represent registration status, lucrativeness of trademark, and molecule submarket, respectively. The standard errors are clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table 4: Effect of litigation experience on number of infringing trademarks

Selected Independent Variables	M1 NBREG	M2 NBREG	M3 NBREG CF Approach	M4 NBREG
	(1)	(2)	(3)	(4)
Litigation Experience	0.9745	1.0588	0.8125	1.0653
	(0.0796)	(0.0763)	(0.1826)	(0.0744)
Litigation Experience * Dummy for Registered Trademark	1.0225	1.0049	1.1251	1.0090
	(0.0934)	(0.0955)	(0.0863)	(0.0935)
Litigation Experience * Dummy for Lucrative Trademark	0.9968	0.9723	1.1769	0.9627
	(0.1035)	(0.0775)	(0.3257)	(0.0742)
Litigation Experience * Dummy for Lucrative Molecule Submarket	0.9291*	0.9187**	0.8875*	0.9156**
	(0.0403)	(0.0312)	(0.0584)	(0.0314)
Residual from Litigation Experience First Stage Reg			1.4196	
			(0.4148)	
Residual from Litigation Experience interacted with Registration			0.8723	
Status First Stage Reg			(0.0994)	
Residual from Litigation Experience interacted with LTM First			0.8101	
Stage Reg			(0.2389)	
Residual from Litigation Experience interacted with LMM First			1.0435	
Stage Reg			(0.0796)	
Dummy for Registered Trademark	1.7312***	1.9417***	1.8588***	1.9762***
	(0.2740)	(0.3240)	(0.3281)	(0.3469)
Dummy for Lucrative Trademark	1.6168***	1.9087***	1.8141***	1.9207***
	(0.2589)	(0.3248)	(0.3213)	(0.3307)
Dummy for Lucrative Molecule Submarket	0.8531	1.0067	1.0155	1.0194
	(0.1084)	(0.1425)	(0.1508)	(0.1447)
Constant	0.1415***	0.3823***	0.3951***	6.336
	(0.0298)	(0.1359)	(0.1422)	(31.0208)
Other Control Variables	Number of Patents, Defense Experience and its interaction with Registration Status, LTM, and LMM, MRP distance, and Firm age (in months)			
Fixed Effects				
Therapeutic Market	No	Yes	Yes	No
Month	No	Yes	Yes	Yes
Firm	No	Yes	Yes	No
Therapeutic Market * Year	No	No	No	Yes
Firm * Year	No	No	No	Yes
Observations	97,622	97,622	97,622	97,622
Log Likelihood	-48094	-48094	-48937	-48094
Standard Errors	Clustered at Firm level			

Notes: The table reports the estimated incidence ratio of primary independent variables – namely litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket – with number of infringing trademarks as the dependent variable. Column 2 reports the estimated ratio of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 4 reports the same with year-varying firm and therapeutic market fixed effects. In Column 3, we implemented a control function approach to resolve endogeneity concerns. Following Wooldridge ,2010, we estimate the residuals from the first-stage regressions with litigation experience, its interaction with Reg Status, LTM, and LMM as the dependent variables. The independent variables constitute the set of instruments namely – (a) number of ANDA approval, (b) cumulative total of ANDA approval, (c) interaction term of (a) with Reg Status, LTM, and LMM, in addition to the control variables. We plug the residuals of these four endogenous variables in the second stage. From Column 3, none of these residual terms are statistically significant revealing the absence of endogeneity problem. Therefore, we use the estimated coefficients in Column 2 to infer the effects of litigation experience. Reg status, LTM, and LMM represent registration status, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table 5: Comparison of real revenue generated by litigating and non-litigating firms

Litigation experience	Number of firms	Mean annual revenue [real in US $]
Litigation	29	1,685,545
		[248,142]
No Litigation	296	446,231
		[37,681]
Difference between firms with litigation		1,239,314***
and no litigation experience		[139,752]

Notes: The table reports the real revenue generated by firms averaged across years and its standard error [in parentheses]. The revenue was converted from nominal to real revenue using the GDP implicit deflator with 2011 as the base year provided by the World Bank [Accessed from `https://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG?locations=IN`]. We also converted the real revenue from the local currency [INR] to US dollars [US $] by dividing the real revenue with a value of 73.44. Additionally, *Litigation* denotes firms with at least one litigation experience and *No Litigation* denotes firms with zero litigation experience. The sign *** represents statistical significance at the 1 percent level.

9 Figures

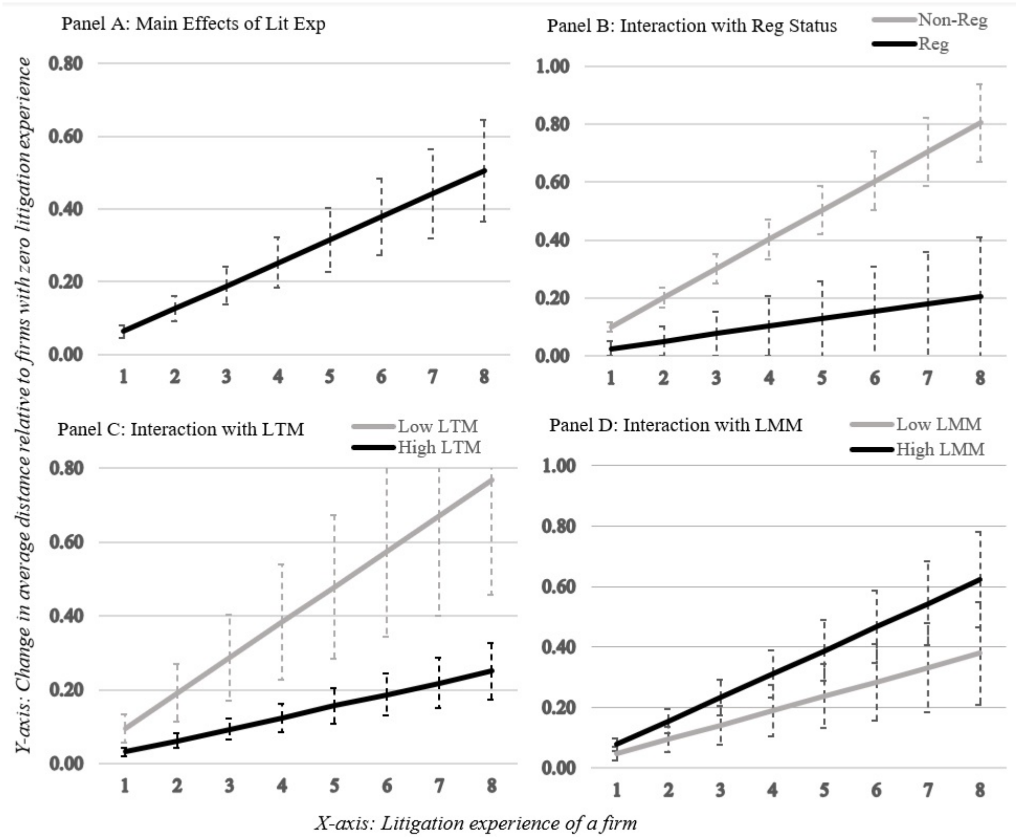

Figure 1: Main and interaction effects of litigation experience on distance of competing trademarks

Notes: In the above figure, we illustrate the marginal effects of litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket provided in Appendix Table A2. The X-axis represents the litigation experience of a firm. The Y-axis represents the difference between the estimated average distance of competing trademarks for firms with non-zero litigation experience relative to those with zero litigation experience. For instance, in Panel A, the coordinate of one in the x-axis represents the change in average distance of competing trademarks of 0.0613 (about 0.5 letters) for firms with one litigation experience relative to those with zero litigation experience. Thus, a value greater than zero indicates that the competitors name their trademarks differently relative to the incumbents' trademarks. From the graphs, it is evident that as firms develop a reputation for being tough litigant causes competitors to name their trademarks differently; in addition, this deterrence effect is more prominent for its trademarks in high lucrative markets (see Panel D). The dashed bars represent the standard errors clustered at the firm level. Lit Exp, Non-Reg, Reg, LTM, and LMM represent litigation experience, non-registered brandnames, registered trademarks, lucrativeness of trademark, and molecule submarket, respectively.

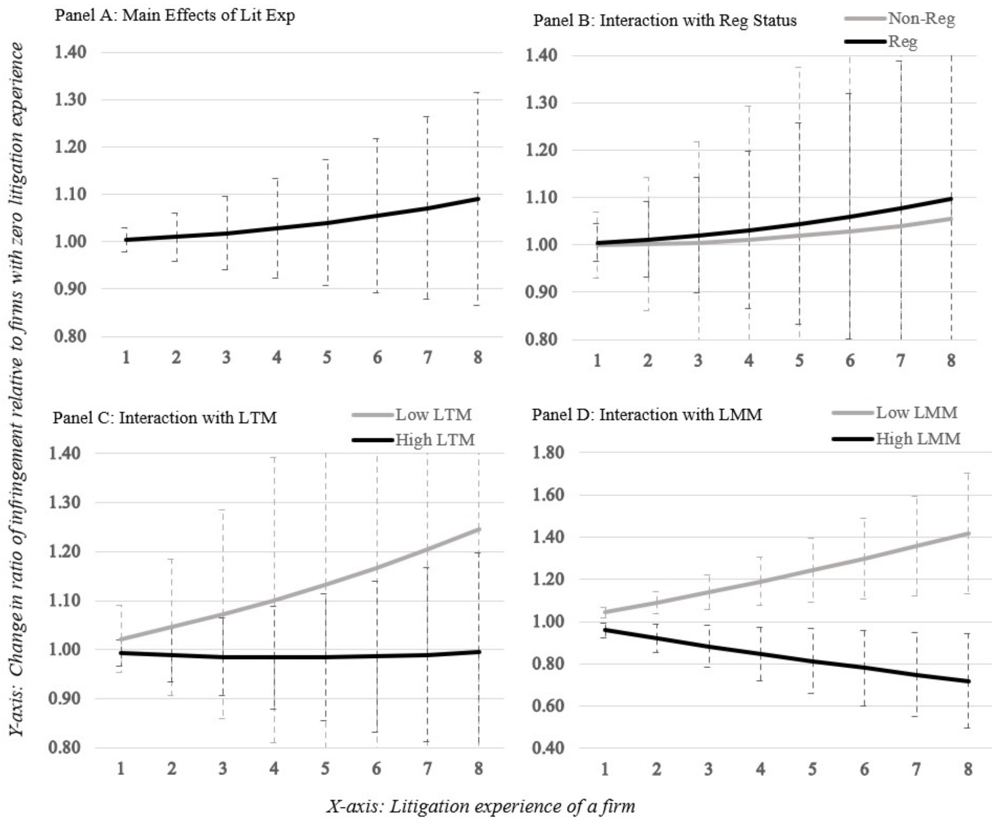

Figure 2: Main and interaction effects of litigation experience on number of infringing trademarks

Notes: In the above figure, we illustrate the marginal effects of litigation experience and its interaction with registration status, lucrativeness of trademarks, and molecule submarket provided in Appendix Table A3. The X-axis represents the litigation experience of a firm. The Y-axis represents the estimated change in the average number of infringing trademarks faced by a firm with non-zero litigation experience and dividing it by the average number of infringing trademarks faced by a firm with zero litigation experience. For instance, in Panel A, the coordinate of one in X-axis represents the estimated ratio of 1.0040 meaning that firms with one litigation experience a similar risk of their trademark being infringed relative to those with zero litigation experience. Thus, a value greater than one indicates a greater risk of being infringed relative to firms with zero litigation experience; whereas a value lower than one indicates a lower risk of being infringed relative to firms with zero litigation experience. The firm's reputation of being a tough litigant provides a deterrence effect for its trademark in the high lucrative market. The dashed bars represent the standard errors clustered at the firm level. Lit Exp, Non-Reg, Reg, LTM, and LMM represent litigation experience, non-registered brandnames, registered trademarks, lucrativeness of trademarks, and molecule submarket, respectively.

10 Appendix Tables

Table A1: Measures of trademark infringement regressed on registration status, lucrativeness of trademark, and market

Selected Independent Variables	Distance of competing trademarks LSDV			Number of infringing trademarks NREG		
	(1)	(2)	(3)	(4)	(5)	(6)
Dummy for Registered Trademark	-0.5402***	-0.5401***	-0.3517***	1.7447***	1.7447***	1.5667**
	(0.0075)	(0.0659)	(0.0880)	(0.0337)	(0.2609)	(0.3097)
Dummy for Lucrative Trademark	-0.0853***	-0.0853	-0.0015	1.7036***	1.7036***	1.6578**
	(0.0090)	(0.0683)	(0.1057)	(0.0347)	(0.2855)	(0.4016)
Dummy for Lucrative Molecule Submarket	0.2139***	0.2139***	0.3231***	0.9124***	0.9124	0.8175
	(0.0074)	(0.0678)	(0.0928)	(0.0165)	(0.1221)	(0.1728)
Dummy for Registered Trademark *			-0.1606			1.0538
Dummy for Lucrative Trademark			(0.1081)			(0.2528)
Dummy for Registered Trademark *			-0.2089**			1.1973
Dummy for Lucrative Molecule Submarket			(0.1060)			(0.3057)
Constant	6.3178***	6.3178***	6.2351***	0.7293	0.7293	0.7714
	(0.1404)	(0.1803)	(0.1829)	(0.2453)	(0.2490)	(0.2708)
Other Control Variables	Number of Patents, MRP distance and Firm age (in months)					
Fixed Effects						
Therapeutic Market	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Observations	97,622	97,622	97,622	97,622	97,622	97,622
R-square	0.2797	0.2797	0.2827		-	
Log-likelihood		-		-49,129	-49,129	-49,115
Standard Errors	Robust	Clustered at Firm level		Robust	Clustered at Firm level	

Notes: The table reports the coefficients of primary independent variables - namely registration status, lucrativeness of trademark, and molecule submarket - estimated with the model specified in Equation 1 under section 4.1. Columns 1 to 3 report the coefficients with the distance of competing trademarks as the dependent variable and are estimated with the least square dummy variable (LSDV) model. Columns 4 to 6 report the incidence ratio with the number of infringing trademarks as the dependent variable and are estimated with the negative binominal (NBREG) regression model. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A2: Main and interaction effects of litigation experience on distance of competing trademarks

Selected Independent Variables	Main Effects	Interactions					
		Non-Reg	Reg	Low LTM	High LTM	Low LMM	High LMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Registered (relative to Non-Registered Trademarks)	-0.5340***						
	(0.0655)						
Dummy for High LTM (relative to Low LTM)	-0.0597						
	(0.0683)						
Dummy for High LMM (relative to Low LMM)	0.1429**						
	(0.0630)						
Litigation Experience of 1 [relative to Zero Experience]	0.0631***	0.1006***	0.0255	0.0959**	0.0312***	0.0474**	0.0778***
	(0.0175)	(0.0169)	(0.0259)	(0.0388)	(0.0100)	(0.0212)	(0.0198)
Litigation Experience of 2 [relative to Zero Experience]	0.1262***	0.2012***	0.0510	0.1917**	0.0624***	0.0949**	0.1557***
	(0.0350)	(0.0337)	(0.0517)	(0.0776)	(0.0191)	(0.0424)	(0.0396)
Litigation Experience of 3 [relative to Zero Experience]	0.1893***	0.3018***	0.0766	0.2876**	0.0936***	0.1423**	0.2335***
	(0.0525)	(0.0506)	(0.0776)	(0.1164)	(0.0287)	(0.0636)	(0.0594)
Litigation Experience of 4 [relative to Zero Experience]	0.2524***	0.4024***	0.1021	0.3833**	0.1248***	0.1897**	0.3114***
	(0.0700)	(0.0675)	(0.1035)	(0.1552)	(0.0383)	(0.0847)	(0.0792)
Litigation Experience of 5 [relative to Zero Experience]	0.3155***	0.5030***	0.1276	0.4793**	0.1561***	0.2372**	0.3892***
	(0.0875)	(0.0844)	(0.1294)	(0.1941)	(0.0478)	(0.1059)	(0.0990)
Litigation Experience of 6 [relative to Zero Experience]	0.3786***	0.6036***	0.1531	0.5752***	0.1873***	0.2846**	0.4671***
	(0.1050)	(0.1012)	(0.1552)	(0.2329)	(0.0574)	(0.1271)	(0.1188)
Litigation Experience of 7 [relative to Zero Experience]	0.4417***	0.7042***	0.1786	0.6710**	0.2185***	0.3320**	0.5449***
	(0.1225)	(0.1181)	(0.1811)	(0.2717)	(0.0670)	(0.1483)	(0.1386)
Litigation Experience of 8 [relative to Zero Experience]	0.5048***	0.8048***	0.2042	0.7669**	0.2500***	0.3795**	0.6228***
	(0.1400)	(0.1350)	(0.2070)	(0.3105)	(0.0765)	(0.1695)	(0.1583)

Notes: The table reports the main and interaction effects of litigation experience estimated from M2 in Table 3. Lit Exp, Non-Reg, Reg, LTM, and LMM represent litigation experience, non-registered brand names, registered trademarks, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A3: Main and interaction effects of litigation experience on number of infringing trademarks

Selected Independent Variables	Main Effects	Interactions					
		Non-Reg	Reg	Low LTM	High LTM	Low LMM	High LMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Registered (relative to Non-Registered Trademarks)	1.7786***						
	(0.2699)						
Dummy for High LTM (relative to Low LTM)	1.7946***						
	(0.2858)						
Dummy for High LMM (relative to Low LMM)	1.0062***						
	(0.1270)						
Litigation Experience of 1 [relative to Zero Experience]	1.0040***	0.9997***	1.0048***	1.0216***	0.9933***	1.0440***	0.9591***
	(0.0256)	(0.0706)	(0.0398)	(0.0680)	(0.0275)	(0.0243)	(0.0352)
Litigation Experience of 2 [relative to Zero Experience]	1.0100***	1.0014***	1.0116***	1.0455***	0.9884***	1.0901***	0.9200***
	(0.0514)	(0.1411)	(0.0805)	(0.1389)	(0.0539)	(0.0513)	(0.0680)
Litigation Experience of 3 [relative to Zero Experience]	1.0180***	1.0051***	1.0206***	1.0719***	0.9853***	1.1384***	0.8826***
	(0.0777)	(0.2118)	(0.1225)	(0.2131)	(0.0796)	(0.0811)	(0.0986)
Litigation experience of 4 [relative to Zero Experience]	1.0282***	1.0109***	1.0316***	1.1009***	0.9839***	1.1892***	0.8470***
	(0.1046)	(0.2831)	(0.1662)	(0.2912)	(0.1047)	(0.1142)	(0.1270)
Litigation Experience of 5 [relative to Zero Experience]	1.0404***	1.0186***	1.0448***	1.1326***	0.9842***	1.2424***	0.8129***
	(0.1326)	(0.3555)	(0.2119)	(0.3737)	(0.1294)	(0.1508)	(0.1535)
Litigation Experience of 6 [relative to Zero Experience]	1.0548***	1.0284**	1.0602***	1.1671**	0.9861***	1.2982***	0.7804***
	(0.1618)	(0.4296)	(0.2599)	(0.4613)	(0.1539)	(0.1912)	(0.1781)
Litigation Experience of 7 [relative to Zero Experience]	1.0714***	1.0402**	1.0779***	1.2048**	0.9897***	1.3569***	0.7493***
	(0.1926)	(0.5057)	(0.3106)	(0.5545)	(0.1783)	(0.2359)	(0.2010)
Litigation Experience of 8 [relative to Zero Experience]	1.0903***	1.0542*	1.0979***	1.2456*	0.9950***	1.4184***	0.7195***
	(0.2253)	(0.5842)	(0.3645)	(0.6542)	(0.2029)	(0.2851)	(0.2223)

Notes: The table reports the main and interaction effects of litigation experience estimated from M2 in Table 4. Lit Exp, Non-Reg, Reg, LTM, and LMM represent litigation experience, non-registered brand names, registered trademarks, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A4: Effect of lagged litigation experience on distance of competing trademarks

Selected Independent Variables [Lagged by a month]	M1 LSDV	M2 IV 2SLS	M3 IV GMM	M4 LSDV
	(1)	(2)	(3)	(4)
Litigation Experience	0.1217****	0.1274***	0.1499***	0.1053***
	(0.0358)	(0.0457)	(0.0371)	(0.0403)
Litigation Experience * Dummy for Registered Trademark	-0.0757***	-0.1105***	-0.1190***	-0.0725***
	(0.0271)	(0.0344)	(0.0309)	(0.0278)
Litigation Experience * Dummy for Lucrative Trademark	-0.0674	-0.0630	-0.0894**	-0.0709
	(0.0457)	(0.0574)	(0.0417)	(0.0462)
Litigation Experience * Dummy for Lucrative Molecule Submarket	0.0297	0.0558	0.0846***	0.0293
	(0.0217)	(0.0426)	(0.0305)	(0.0220)
Dummy for Registered Trademark	-0.5335***	-0.5209***	-0.5463***	-0.5547***
	(0.0653)	(0.0630)	(0.0599)	(0.0660)
Dummy for Lucrative Trademark	-0.0180	-0.0196	-0.0328	-0.0162
	(0.0737)	(0.0761)	(0.0703)	(0.0730)
Dummy for Lucrative Molecule Submarket	0.1728**	0.1630**	0.1234*	0.1712**
	(0.0696)	(0.0682)	(0.0635)	(0.0711)
Constant	7.8418***			7.8465***
	(0.0561)			(0.0583)
Other Control Variables	Number of Patents, Defense Experience and its interaction with Registration Status, LTM, and LMM, MRP distance, and Firm age (in months)			
Tests for IV Regression				
Endogenity Test [Chi Square P Value]		*0.4509*		
Weak Identification Test [Kleibregen-Paap rk Wald F Statistic]		*22.421*		
Over Identification Test [Hansen J Statistic P-Value]		*0.2685*		
Fixed Effects				
Therapeutic Market	Yes	Yes	Yes	No
Month	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	No
Therapeutic Market * Year	No	No	No	Yes
Firm * Year	No	No	No	Yes
Observations	95,624	95,624	95,624	95,587
R-square	0.282	0.068	0.067	0.299
Standard Errors	Clustered at Firm level			

Notes: The table reports the estimated coefficients of lagged primary independent variables – namely litigation experience and its interaction with registration status, the lucrativeness of trademark, and molecule submarket – with distance of competing trademarks as the dependent variable. All the independent variables were lagged by a month to estimate their effects on the dependent variable in the above regressions. Column 1 reports the estimated coefficients of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 4 reports the estimated coefficients of the model with year-varying firm and therapeutic market fixed effects. Columns 2 and 3 report the estimated coefficients from the instrumental variable approach with 2SLS and GMM, respectively. We implemented an instrumental variable approach to resolve endogeneity concerns regarding our primary variable of interest – litigation experience and its interactions. The endogenous variables are lagged terms of litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket. The instruments constitute lagged terms of (a) number of ANDA approval, (b) cumulative total of ANDA approval, (c) square term of (a) and (b), (d) interactions of (a) and (b) with registration status, lucrativeness of trademark and molecule submarket. The endogeneity test fails to reject the null hypothesis that the instrumented variables are exogenous (p-value = 0.4509). Reg status, LTM, and LMM represent registration status, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A5: Effect of litigation experience on distance of competing trademarks - Subsample of molecules without expiring patents

Selected Independent Variables	M1 LSDV	M2 IV 2SLS	M3 IV GMM	M4 LSDV
	(1)	(2)	(3)	(4)
Litigation Experience	0.1391***	0.1460***	0.1653***	0.1295***
	(0.0331)	(0.0428)	(0.0315)	(0.0334)
Litigation Experience * Dummy for Registered Trademark	-0.0800***	-0.1101**	-0.1298***	-0.0772***
	(0.0286)	(0.0455)	(0.0413)	(0.0292)
Litigation Experience * Dummy for Lucrative Trademark	-0.0974**	-0.0947	-0.1018**	-0.1011**
	(0.0451)	(0.0693)	(0.0449)	(0.0460)
Litigation Experience * Dummy for Lucrative Molecule Submarket	0.0345**	0.0620	0.0709**	0.0341**
	(0.0156)	(0.0460)	(0.0349)	(0.0158)
Dummy for Registered Trademark	-0.5146***	-0.5032***	-0.5475***	-0.5351***
	(0.0711)	(0.0669)	(0.0604)	(0.0717)
Dummy for Lucrative Trademark	-0.0079	-0.0092	-0.0331	-0.0056
	(0.0766)	(0.0791)	(0.0732)	(0.0762)
Dummy for Lucrative Molecule Submarket	0.2661***	0.2557***	0.2150***	0.2619***
	(0.0749)	(0.0737)	(0.0678)	(0.0767)
Constant	7.8019***			7.8078***
	(0.0637)			(0.0647)
Other Control Variables	Number of Patents, Defense Experience and its interaction with Registration Status, LTM, and LMM, MRP distance, and Firm age (in months)			
Tests for IV Regression				
Endogenity Test [Chi Square P Value]	*0.8046*			
Weak Identification Test [Kleibregen-Paap rk Wald F Statistic]	*14.396*			
Over Identification Test [Hansen J Statistic P-Value]	*0.2322*			
Fixed Effects				
Therapeutic Market	Yes	Yes	Yes	No
Month	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	No
Therapeutic Market * Year	No	No	No	Yes
Firm * Year	No	No	No	Yes
Observations	88,150	88,150	88,150	88,102
R-square	0.297	0.073	0.071	0.316
Standard Errors	Clustered at Firm level			

Notes: The table reports the estimated coefficients of primary independent variables – namely litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket – with the distance of competing trademarks as the dependent variable. We take the subsample of molecules without expiring patents to negate the possibility of patent expiry influencing the firm's decision to protect its core market, if any, through litigation strategies. Column 1 reports the estimated coefficients of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 4 reports the estimated coefficients of the model with year-varying firm and therapeutic market fixed effects. Columns 2 and 3 report the estimated coefficients from the instrumental variable approach with 2SLS and GMM, respectively. We implemented an instrumental variable approach to resolve any endogeneity concern. The endogenous variables are litigation experience and its interaction with registration status, the lucrativeness of trademark, and molecule submarket. The instruments constitute (a) number of ANDA approval, (b) cumulative total of ANDA approval, (c) square term of (a) and (b), (d) interactions of (a) and (b) with registration status, lucrativeness of trademark and molecule submarket. The endogeneity test fails to reject the null hypothesis that the instrumented variables are exogenous (p-value = 0.8046). Reg status, LTM, and LMM represent registration status, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A6: Effect of litigation experience on distance of competing trademarks - Subsample of registered trademarks

Selected Independent Variables	M1 LSDV	M2 IV 2SLS	M3 IV GMM	M4 LSDV
	(1)	(2)	(3)	(4)
Litigation Experience	0.0244	0.0158	0.0419	0.0009
	(0.0379)	(0.0433)	(0.0337)	(0.0372)
Litigation Experience * Dummy for Lucrative Trademark	0.0020	-0.0141	0.0718*	0.0053
	(0.0403)	(0.0600)	(0.0395)	(0.0395)
Litigation Experience * Dummy for Lucrative Molecule Submarket	-0.0047	0.0474	0.1321***	-0.0060
	(0.0226)	(0.0601)	(0.0312)	(0.0231)
Dummy for Lucrative Trademark	-0.1271	-0.1242	-0.0969	-0.1314
	(0.0822)	(0.0824)	(0.0806)	(0.0800)
Dummy for Lucrative Molecule Submarket	0.1393	0.1141	0.0237	0.1430
	(0.1040)	(0.1009)	(0.0855)	(0.1060)
Constant	7.4055***			7.3963***
	(0.0658)			(0.0643)
Other Control Variables	Number of Patents, Defense Experience and its interaction with LTM, and LMM, MRP distance, and Firm age (in months)			
Tests for IV Regression				
Endogenity Test [Chi Square P Value]		*0.0137*		
Weak Identification Test [Kleibregen-Paap rk Wald F Statistic]		*53.498*		
Over Identification Test [Hansen J Statistic P-Value]		*0.1713*		
Fixed Effects				
Therapeutic Market	Yes	Yes	Yes	No
Month	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	No
Therapeutic Market * Year	No	No	No	Yes
Firm * Year	No	No	No	Yes
Observations	44,577	44,577	44,577	44,562
R-square	0.332	0.014	0.000	0.356
Standard Errors	Clustered at Firm level			

Notes: The table reports the estimated coefficients of primary independent variables – namely litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket – with the distance of competing trademarks as the dependent variable. We take the subsample of registered trademarks here to tackle any concern about reverse causality between the decision to register the trademarks and the intensity of trademark infringement. Column 1 reports the estimated coefficients of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 4 reports the estimated coefficients of the model with year-varying firm and therapeutic market fixed effects. Columns 2 and 3 report the estimated coefficients from the instrumental variable approach with 2SLS and GMM, respectively. We implemented an instrumental variable approach to resolve any endogeneity concern arising from omitted variable bias. The endogenous variables are litigation experience and its interaction with lucrativeness of trademark, and molecule submarket. The instruments constitute (a) number of ANDA approval, (b) cumulative total of ANDA approval, (c) square term of (a) and (b), (d) interactions of (a) and (b) with lucrativeness of trademark and molecule submarket. The endogenity test rejects the null hypothesis indicating that the primary variable of interest is endogenous (p-value = 0.0137). The instruments are valid, thereby enabling us to derive consistent estimates from the IV regressions. The estimated coefficients of litigation experience and its interactions reported in Columns 2 and 3 are qualitatively similar to those estimated in the full model reported in Column 2 in Table 3 - indicative of a smaller magnitude of endogeneity resulting in similar coefficients in LSDV and IV models. LTM, and LMM represent the lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A7: Effect of litigation experience on *median* distance of competing trademarks

Selected Independent Variables	M1 LSDV	M2 IV 2SLS	M3 IV GMM	M4 LSDV
	(1)	(2)	(3)	(4)
Litigation Experience	0.1129***	0.1451***	0.1439***	0.1014***
	(0.0375)	(0.0500)	(0.0350)	(0.0387)
Litigation Experience * Dummy for Registered Trademark	-0.1001***	-0.1384***	-0.1576***	-0.0966***
	(0.0352)	(0.0396)	(0.0340)	(0.0359)
Litigation Experience * Dummy for Lucrative Trademark	-0.0486	-0.0681	-0.0590	-0.0547
	(0.0499)	(0.0725)	(0.0431)	(0.0502)
Litigation Experience * Dummy for Lucrative Molecule Submarket	0.0307	0.0648	0.0841**	0.0300
	(0.0234)	(0.0499)	(0.0338)	(0.0240)
Dummy for Registered Trademark	-0.6163***	-0.6020***	-0.6372***	-0.6435***
	(0.0768)	(0.0750)	(0.0716)	(0.0775)
Dummy for Lucrative Trademark	0.0080	0.0123	-0.0035	0.0104
	(0.0893)	(0.0920)	(0.0871)	(0.0883)
Dummy for Lucrative Molecule Submarket	0.2809***	0.2693***	0.2126***	0.2766***
	(0.0880)	(0.0865)	(0.0771)	(0.0900)
Constant	7.5807***			7.5968***
	(0.0645)			(0.0658)
Other Control Variables	Number of Patents, Defense Experience and its interaction with Registration Status, LTM, and LMM, MRP distance, and Firm age (in months)			
Tests for IV Regression				
Endogenity Test [Chi Square P Value]		*0.4113*		
Weak Identification Test [Kleibregen-Paap rk Wald F Statistic]		*20.447*		
Over Identification Test [Hansen J Statistic P-Value]		*0.2412*		
Fixed Effects				
Therapeutic Market	Yes	Yes	Yes	No
Month	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	No
Therapeutic Market * Year	No	No	No	Yes
Firm * Year	No	No	No	Yes
Observations	97,622	97,622	97,622	97,577
R-square	0.250	0.064	0.063	0.269
Standard Errors	Clustered at Firm level			

Notes: The table reports the estimated coefficients of primary independent variables – namely litigation experience and its interaction with registration status, lucrativeness of trademark and molecule submarket – with *median* distance of competing trademarks as the dependent variable. Column 1 reports the estimated coefficients of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 4 reports the estimated coefficients of the model with year-varying firm and therapeutic market fixed effects. Columns 2 and 3 report the estimated coefficients from the instrumental variable approach with 2SLS and GMM, respectively. We implemented an instrumental variable approach to resolve any endogeneity concern arising from the omitted variable bias. The endogenous variables are litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket. The instruments constitute (a) number of ANDA approval, (b) cumulative total of ANDA approval, (c) square term of (a) and (b), (d) interactions of (a) and (b) with registration status, lucrativeness of trademark and molecule submarket. The endogeneity test fails to reject the null hypothesis that the instrumented variables are exogenous (p-value = 0.4113). Given this, we rely upon the estimated coefficients from Column 2 to infer the effect of litigation experience on the [median] distance of competing trademarks. Reg status, LTM, and LMM represent registration status, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A8: Effect of [*categorical*] litigation experience on distance of competing trademarks

Selected Independent Variables	M1 LSDV	M2 LSDV	M3 LSDV
	(1)	(2)	(3)
Litigation Experience of 1 [relative to Zero Experience]	0.2082	0.3117*	0.2049
	(0.2540)	(0.1817)	(0.3346)
Litigation Experience of 2 [relative to Zero Experience]	-0.0516	0.0831	-0.0184
	(0.1463)	(0.1651)	(0.2244)
Litigation Experience of 3 [relative to Zero Experience]	-0.0511	0.3214	0.1890
	(0.1539)	(0.2514)	(0.2566)
Litigation Experience of 4 and 5 [relative to Zero Experience]	1.0042***	1.0967***	0.8957**
	(0.3381)	(0.4114)	(0.4199)
Litigation Experience of 6 [relative to Zero Experience]	1.0599***	1.1210***	0.9181***
	(0.0553)	(0.1530)	(0.1871)
Litigation Experience of 7 [relative to Zero Experience]	1.0069***	1.0790***	0.8824***
	(0.0552)	(0.1536)	(0.1884)
Litigation Experience of 8 [relative to Zero Experience]	1.1443***	1.3363***	1.1697***
	(0.1596)	(0.1453)	(0.2302)
Dummy for Registered Trademark	-0.4745***	-0.5476***	-0.5697***
	(0.0657)	(0.0649)	(0.0657)
Dummy for Lucrative Trademark	0.1039	-0.0194	-0.0153
	(0.0686)	(0.0750)	(0.0739)
Dummy for Lucrative Molecule Submarket	0.2690***	0.2111***	0.2091***
	(0.0697)	(0.0728)	(0.0744)
Constant	7.6070***	7.8056***	7.8238***
	(0.0710)	(0.0592)	(0.0627)
Other Primary Independent Variables	Interaction of Litigation Experience with Reg status, LTM, and LMM		
Other Control Variables	Number of Patents, Defense Experience and its interaction with Registration Status, LTM, and LMM, MRP distance, and Firm age (in months)		
Fixed Effects			
Therapeutic Market	No	Yes	No
Month	NO	Yes	Yes
Firm	No	Yes	No
Therapeutic Market * Year	No	No	Yes
Firm * Year	No	No	Yes
Observations	97,622	97,622	97,577
R-square	0.075	0.289	0.307
Standard Errors	Clustered at Firm level		

Notes: The table reports the estimated coefficients of primary independent variables – namely litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket – with the distance of competing trademarks as the dependent variable. Here, we treat the litigation experience as a categorical variable and estimate the regressions. Column 2 reports the estimated coefficients of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 3 reports the estimated coefficients of the model with year-varying firm and therapeutic market fixed effects. Reg Status, LTM, and LMM represent registration status, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively

Table A9: Main and interaction effect of [*categorical*] litigation experience on distance of competing trademarks

Selected Independent Variables	Main Effects	Interactions					
		Non-Reg	Reg	Low LTM	High LTM	Low LMM	High LMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Registered (relative to Non-Registered Trademarks)	-0.5256***						
	(0.0640)						
Dummy for High LTM (relative to Low LTM)	-0.0667						
	(0.0667)						
Dummy for High LMM (relative to Low LMM)	0.1412**						
	(0.0628)						
Litigation experience of 1 [relative to Zero Experience]	0.1289	-0.1162	0.3747**	0.3143**	-0.0514	0.3715**	-0.0993
	(0.0879)	(0.0967)	(0.1734)	(0.1270)	(0.1313)	(0.1694)	(0.1568)
Litigation Experience of 2 [relative to Zero Experience]	0.1740	0.2868*	0.0610	-0.0169	0.3600**	0.1613	0.1861
	(0.1097)	(0.1506)	(0.1553)	(0.1738)	(0.1720)	(0.1270)	(0.1461)
Litigation Experience of 3 [relative to Zero Experience]	0.2855*	0.3405*	0.2303	0.2458	0.3241**	0.3061	0.2661*
	(0.1558)	(0.1765)	(0.2365)	(0.2519)	(0.1491)	(0.2042)	(0.1378)
Litigation Experience of 4 and 5 [relative to Zero Experience]	0.6307***	0.8282***	0.4327*	0.8753**	0.3926***	0.6546**	0.6082***
	(0.2316)	(0.2369)	(0.2590)	(0.4035)	(0.1437)	(0.2573)	(0.2234)
Litigation Experience of 6 [relative to Zero Experience]	0.6909***	0.9759***	0.4053***	0.9426***	0.4460***	0.5845***	0.7912***
	(0.1451)	(0.1449)	(0.1498)	(0.1480)	(0.1492)	(0.1510)	(0.1471)
Litigation Experience of 7 [relative to Zero Experience]	0.6847***	0.9395***	0.4294***	0.9586***	0.4181***	0.5504***	0.8112***
	(0.1451)	(0.1454)	(0.1497)	(0.1480)	(0.1491)	(0.1509)	(0.1470)
Litigation Experience of 8 [relative to Zero Experience]	0.9370***	1.1725***	0.7008***	1.3900***	0.4960***	0.6477***	1.2091***
	(0.1558)	(0.1795)	(0.1756)	(0.1712)	(0.1686)	(0.1396)	(0.1871)

Notes: The table reports the main and interaction effects of litigation experience, treated as a categorical variable, estimated from M2 in Appendix Table A8. Lit Exp, Non-Reg, Reg, LTM, and LMM represent litigation experience, non-registered brand names, registered trademarks, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A10: Effect of lagged litigation experience on number of infringing trademarks

Selected Independent Variables [Lagged by a month]	M1 NBREG	M2 NBREG	M3 NBREG CF Approach	M4 NBREG
	(1)	(2)	(3)	(4)
Litigation Experience	0.9721	1.0578	0.8054	1.0255
	(0.0830)	(0.0793)	(0.1836)	(0.0843)
Litigation Experience * Dummy for Registered Trademark	1.0232	1.0054	1.1300	1.0096
	(0.0945)	(0.0968)	(0.0870)	(0.0948)
Litigation Experience * Dummy for Lucrative Brand	0.9980	0.9732	1.1869	0.9631
	(0.1063)	(0.0793)	(0.3374)	(0.0755)
Litigation Experience * Dummy for Lucrative Molecule Submarket	0.9278*	0.9171**	0.8856*	0.9138***
	(0.0408)	(0.0314)	(0.0571)	(0.0316)
Residual from Litigation Experience First Stage Reg			1.4292	
			(0.4261)	
Residual from Litigation Experience interacted with Registration Status First Stage Reg			0.8675	
			(0.0946)	
Residual from Litigation Experience interacted with LTM First Stage Reg			0.8034	
			(0.2433)	
Residual from Litigation Experience interacted with LMM First Stage Reg			1.0449	
			(0.0772)	
Dummy for Registered Trademark	1.7299***	1.9394***	1.8535***	1.9730***
	(0.2742)	(0.3246)	(0.3282)	(0.3475)
Dummy for Lucrative Trademark	1.6135***	1.9128***	1.8151***	1.9245***
	(0.2585)	(0.3269)	(0.3243)	(0.3329)
Dummy for Lucrative Molecule Submarket	0.8539	1.0072	1.0162	1.0202
	(0.1085)	(0.1427)	(0.1512)	(0.1449)
Constant	0.1423***	0.4207***	0.4351***	9.9862
	(0.0301)	(0.1499)	(0.1572)	(48.9550)
Other Control Variables	Number of Patents, Defense Experience and its interaction with Registration Status, LTM, and LMM, MRP distance, and Firm age (in months)			
Fixed Effects				
Therapeutic Market	No	Yes	Yes	No
Month	No	Yes	Yes	Yes
Firm	No	Yes	Yes	No
Therapeutic Market * Year	No	No	No	Yes
Firm * Year	No	No	No	Yes
Observations	95,624	95,624	95,624	95,624
Log Likelihood	-48,111	-48,111	-48,111	-48,111
Standard Errors	Clustered at Firm level			

Notes: The table reports the estimated incidence ratio of primary independent variables – namely lagged litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket – with the number of infringing trademarks as the dependent variable. Column 2 reports the ratio of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 4 reports the same with year-varying firm and therapeutic market fixed effects. In Column 3, we implemented a control function approach to resolve any endogeneity concern arising from the omitted variable bias. Following Wooldridge ,2010, we estimate the residuals from the first-stage regressions with litigation experience, and its interaction with Reg Status, LTM, and LMM as the dependent variables. The independent variables constitute the set of instruments namely – (a) number of ANDA approval, (b) cumulative total of ANDA approval, (c) interaction term of (a) with Reg Status, LTM, and LMM, in addition to the control variables. We plug the residuals of these four endogenous variables in the second stage. From Column 3, none of these residual terms are statistically significant revealing the absence of endogeneity. Therefore, we use the estimated coefficients in Column 2 to infer the effects of litigation experience. Reg, LTM, and LMM represent litigation experience, non-registered brand names, registered trademarks, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A11: Effect of litigation experience on number of infringing trademarks - Subsample of molecules without expiring patents

Selected Independent Variables	M1 NBREG	M2 NBREG	M3 NBREG CF Approach	M4 NBREG
	(1)	(2)	(3)	(4)
Litigation Experience	1.0233	1.0938	0.9300	1.1171*
	(0.0829)	(0.0705)	(0.2250)	(0.0645)
Litigation Experience * Dummy for Registered Trademark	0.9947	0.9742	1.0527	0.9821
	(0.0776)	(0.0866)	(0.0986)	(0.0833)
Litigation Experience * Dummy for Lucrative Trademark	0.9790	0.9671	1.0362	0.9498
	(0.0997)	(0.0787)	(0.3275)	(0.0721)
Litigation Experience * Dummy for Lucrative Molecule Submarket	0.8627***	0.8497***	0.8246**	0.8443***
	(0.0479)	(0.0357)	(0.0738)	(0.0368)
Residual from Litigation Experience First Stage Reg			1.3070	
			(0.4084)	
Residual from Litigation Experience interacted with Registration			0.9016	
Status First Stage Reg			(0.1058)	
Residual from Litigation Experience interacted with LTM First			0.9275	
Stage Reg			(0.3064)	
Residual from Litigation Experience interacted with LMM First			1.0405	
Stage Reg			(0.1004)	
Dummy for Registered Trademark	1.6306***	1.8313***	1.7747***	1.8514***
	(0.2698)	(0.3139)	(0.3192)	(0.3351)
Dummy for Lucrative Trademark	1.6395***	1.9501***	1.9112***	1.9736***
	(0.2530)	(0.3138)	(0.3179)	(0.3196)
Dummy for Lucrative Molecule Submarket	0.8032*	0.9603	0.9708	0.9747
	(0.1034)	(0.1377)	(0.1469)	(0.1397)
Constant	0.1495***	0.3875***	0.3958**	235.6727
	(0.0309)	(0.1419)	(0.1466)	(1103.4825)
Other Control Variables	Number of Patents, Defense Experience and its interaction with Registration Status, LTM, and LMM, MRP distance, and Firm age (in months)			
Fixed Effects				
Therapeutic Market	No	Yes	Yes	No
Month	No	Yes	Yes	Yes
Firm	No	Yes	Yes	No
Therapeutic Market * Year	No	No	No	Yes
Firm * Year	No	No	No	Yes
Observations	88,150	88,150	88,150	88,150
Log Likelihood	-43,145	-43,145	-43,145	-43,145
Standard Errors	Clustered at Firm level			

Notes: The table reports the estimated incidence ratio of primary independent variables – namely litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket – with the number of infringing trademarks as the dependent variable. We take the subsample of molecules without expiring patents to rule out the possibility of patent expiry in influencing the firms to protect their core market through litigation strategy. Column 2 reports the estimated coefficients of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 4 reports the same with year-varying firm and therapeutic market fixed effects. In Column 3, we implemented a control function approach to resolve any endogeneity concern arising from the omitted variable bias. Following Wooldridge ,2010, we estimate the residuals from the first-stage regressions with litigation experience, its interaction with Reg Status, LTM, and LMM as the dependent variables. The independent variables constitute the set of instruments namely – (a) number of ANDA approval, (b) cumulative total of ANDA approval, (c) interaction term of (a) with Reg Status, LTM, and LMM, in addition to the control variables. We plug the residuals of these four endogenous variables in the second stage. From Column 3, none of these residual terms are statistically significant revealing an absence of endogeneity. Therefore, we use the estimated coefficients in Column 2 to infer the effects of litigation experience. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A12: Effect of litigation experience on number of infringing trademarks - Subsample of registered trademarks

Selected Independent Variables	M1 NBREG	M2 NBREG	M3 NBREG CF Approach	M4 NBREG
	(1)	(2)	(3)	(4)
Litigation Experience	0.7644*	0.9413	0.6722**	0.9849
	(0.1130)	(0.1579)	(0.1440)	(0.1546)
Litigation Experience * Dummy for Lucrative Trademark	1.3206*	1.1008	1.5285*	1.1023
	(0.2138)	(0.1765)	(0.3330)	(0.1760)
Litigation Experience * Dummy for Lucrative Molecule Submarket	0.9398	0.9081**	0.8976	0.9025***
	(0.0421)	(0.0362)	(0.0712)	(0.0351)
Residual from Litigation Experience First Stage Reg			1.5518*	
			(0.3808)	
Residual from Litigation Experience interacted with LTM First			0.6838	
Stage Reg			(0.1592)	
Residual from Litigation Experience interacted with LMM First			1.0083	
Stage Reg			(0.0764)	
Dummy for Lucrative Trademark	1.2412	1.9812***	1.7805***	2.0014***
	(0.2097)	(0.3925)	(0.3963)	(0.4004)
Dummy for Lucrative Molecule Submarket	0.6614**	0.8280	0.8196	0.8333
	(0.1296)	(0.1739)	(0.1853)	(0.1766)
Constant	0.2709***	0.0000***	0.0000	0.0000
	(0.0534)	(0.0000)	(0.0000)	(0.0000)
Other Control Variables	Number of Patents, Defense Experience and its interaction with LTM, and LMM, MRP distance, and Firm age (in months)			
Fixed Effects				
Therapeutic Market	No	Yes	Yes	No
Month	No	Yes	Yes	Yes
Firm	No	Yes	Yes	No
Therapeutic Market * Year	No	No	No	Yes
Firm * Year	No	No	No	Yes
Observations	44,577	44,577	44,577	44,577
Log Likelihood	-26,149	-26,149	-26,149	-26,149
Standard Errors	Clustered at Firm level			

Notes: The table reports the estimated coefficients of primary independent variables – namely litigation experience and its interaction with registration status, lucrativeness of trademark and molecule submarket – with the number of infringing trademarks as the dependent variable. We take the subsample of registered trademarks here to rule out any reverse causality between the decision to register the trademarks and the intensity of trademark infringement. Column 2 reports the estimated coefficients of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 4 reports the same with year-varying firm and therapeutic market fixed effects. In Column 3, we implemented a control function approach to resolve any endogeneity concern arising from the omitted variable bias. Following Wooldridge ,2010, we estimate the residuals from the first-stage regressions with litigation experience, and its interaction with Reg Status, LTM, and LMM as the dependent variables. The independent variables constitute the set of instruments namely – (a) number of ANDA approval, (b) cumulative total of ANDA approval, (c) interaction term of (a) with Reg Status, LTM, and LMM, in addition to the control variables. We plug the residuals of these four endogenous variables in the second stage. The regression estimates reveal that the residual from the first-stage with litigation experience as the dependent variable is statistically significant at a ten percent level – indicative of the presence of endogeneity. The coefficients of the primary variable of interest should be exogenous as the residuals would capture the element correlated with the error term. Given this, we compare the estimated coefficients from the NBREG and CF approach in Columns 2 and 3 respectively. We find the effect of litigation experience and its interactions on the number of infringing trademarks are qualitatively similar. Therefore, we can state that incumbents can deter infringers by developing a reputation for being a tough litigant. In all the reported regressions, we have clustered the standard errors at the firm level and provided them in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A13: Effect of [*categorical*] litigation experience on number of infringing trademarks

Selected Independent Variables	M1 LSDV	M2 LSDV	M3 LSDV
	(1)	(2)	(3)
Litigation Experience of 1 [relative to Zero Experience]	2.4623	1.1622	0.9640
	(1.3497)	(0.3176)	(0.5209)
Litigation Experience of 2 [relative to Zero Experience]	0.7372	0.9408	0.7370
	(0.3852)	(0.4058)	(0.4323)
Litigation Experience of 3 [relative to Zero Experience]	1.2882	1.0694	0.6805
	(0.4517)	(0.6242)	(0.3958)
Litigation Experience of 4 and 5 [relative to Zero Experience]	0.4406^{*}	1.1039	0.6703
	(0.2073)	(0.7607)	(0.4279)
Litigation Experience of 6 [relative to Zero Experience]	0.4579^{***}	0.4755	0.3904^{*}
	(0.0797)	(0.2195)	(0.1943)
Litigation Experience of 7 [relative to Zero Experience]	0.8883	0.8499	0.6986
	(0.1541)	(0.3943)	(0.3520)
Litigation Experience of 8 [relative to Zero Experience]	1.3773	1.0707	0.6770
	(0.7367)	(0.7147)	(0.5777)
Dummy for Registered Trademark	1.7922^{***}	2.0672^{***}	2.1094^{***}
	(0.2932)	(0.3680)	(0.3978)
Dummy for Lucrative Trademark	1.6427^{***}	1.8137^{***}	1.8273^{***}
	(0.2732)	(0.3124)	(0.3192)
Dummy for Lucrative Molecule Submarket	0.8797	1.0014	1.0125
	(0.1159)	(0.1471)	(0.1495)
Constant	0.1422^{***}	0.3868^{**}	7.7953
	(0.0308)	(0.1427)	(37.8759)
Other Primary Independent Variables	Interaction of Litigation Experience with Reg status, LTM, and LMM		
Other Control Variables	Number of Patents, Defense Experience and its interaction with Registration Status, LTM, and LMM, MRP distance, and Firm age (in months)		
Fixed Effects			
Therapeutic Market	No	Yes	No
Month	No	Yes	Yes
Firm	No	Yes	No
Therapeutic Market * Year	No	No	Yes
Firm * Year	No	No	Yes
Observations	97,622	97,622	97,622
Log Likelihood	-47,870	-47,870	-47,870
Standard Errors	Clustered at Firm level		

Notes: The table reports the estimated coefficients of primary independent variables – namely litigation experience and its interaction with registration status, lucrativeness of trademark, and molecule submarket – with the number of infringing trademarks as the dependent variable. Here, we treat the litigation experience as a categorical variable and estimate the regressions. Column 2 reports the estimated coefficients of the primary model with time-invariant firm and therapeutic market fixed effects, whereas Column 3 reports the estimated coefficients of the model with year-varying firm and therapeutic market fixed effects. Reg Status, LTM, and LMM represent registration status, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

Table A14: Main and interaction effect of [*categorical*] litigation experience on number of infringing trademarks

Selected Independent Variables	Main Effects	Interactions					
		Non-Reg	Reg	Low LTM	High LTM	Low LMM	High LMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Registered (relative to Non-Registered Trademarks)	1.7124***						
	(0.2693)						
Dummy for High LTM (relative to Low LTM)	1.8145***						
	(0.2849)						
Dummy for High LMM (relative to Low LMM)	1.0037***						
	(0.1293)						
Litigation Experience of 1 [relative to Zero Experience]	0.7372***	1.3184***	0.4590*	0.5807***	0.8668**	0.8358**	0.6381***
	(0.2402)	(0.2610)	(0.2633)	(0.1639)	(0.3731)	(0.4227)	(0.1548)
Litigation Experience of 2 [relative to Zero Experience]	0.6708***	1.1470**	0.4418**	0.5143**	0.7952**	0.7257**	0.6158***
	(0.2196)	(0.4581)	(0.1744)	(0.2041)	(0.3968)	(0.3140)	(0.2225)
Litigation Experience of 3 [relative to Zero Experience]	0.7516**	1.0612	0.5992**	0.7244**	0.7793**	0.7873**	0.7148*
	(0.3489)	(0.7146)	(0.2662)	(0.3251)	(0.3931)	(0.3561)	(0.3831)
Litigation Experience of 4 and 5 [relative to Zero Experience]	0.8481*	0.8256	0.8636*	1.0343	0.7311*	0.9270*	0.7589*
	(0.4614)	(0.5599)	(0.4447)	(0.6310)	(0.3779)	(0.4759)	(0.4624)
Litigation Experience of 6 [relative to Zero Experience]	0.5583**	0.3768**	0.6447**	0.6031**	0.5263**	0.6464**	0.4551**
	(0.2473)	(0.1664)	(0.2984)	(0.2704)	(0.2360)	(0.2926)	(0.2031)
Litigation Experience of 7 [relative to Zero Experience]	0.6665**	0.5850**	0.6991**	0.7226**	0.6301**	0.8811**	0.4229**
	(0.2972)	(0.2581)	(0.3216)	(0.3272)	(0.2838)	(0.4028)	(0.1902)
Litigation Experience of 8 [relative to Zero Experience]	1.0321**	0.5007*	1.3151**	1.5965*	0.6913**	1.4160**	0.5801*
	(0.4898)	(0.2662)	(0.6615)	(0.9586)	(0.3321)	(0.6847)	(0.3040)

Notes: The table reports the main and interaction effects of litigation experience, treated as a categorical variable, estimated from M2 in Appendix Table A13. Lit Exp, Non-Reg, Reg, LTM, and LMM represent litigation experience, non-registered brand names, registered trademarks, lucrativeness of trademark, and molecule submarket, respectively. The standard errors were clustered at the firm level and reported in parentheses. The symbols ***, **, and * indicate statistical significance at the level of 1 percent, 5 percent, and 10 percent respectively.

11 Appendix Figures

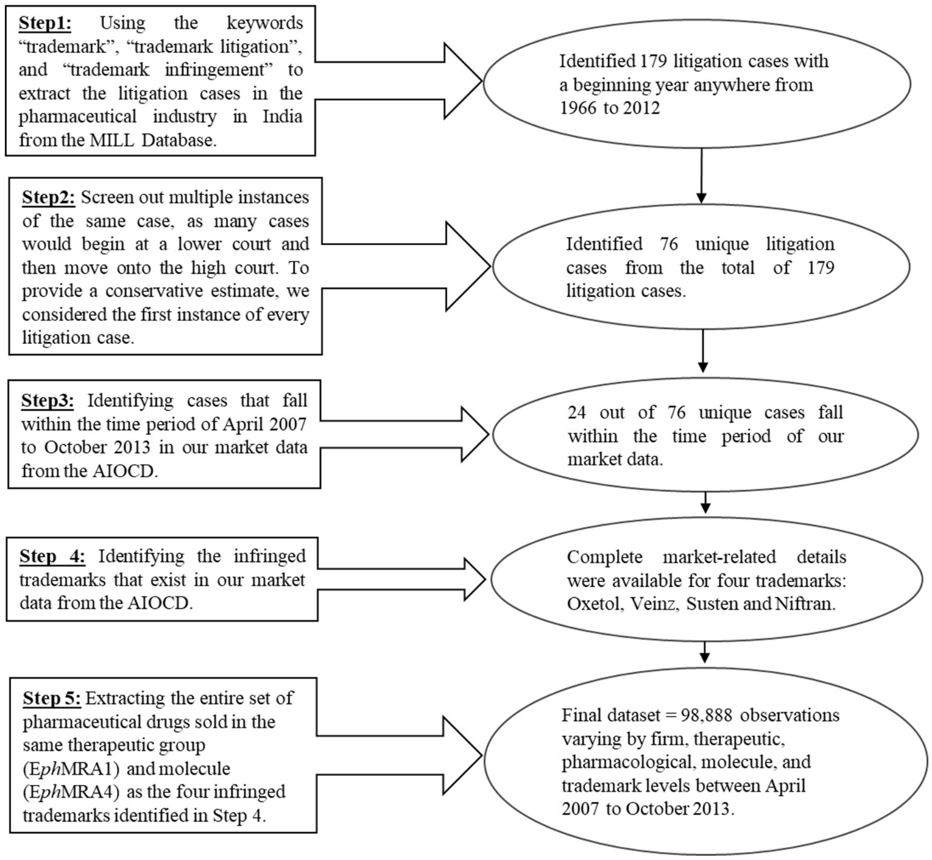

Figure A1: Process involved in the construction of the sample dataset

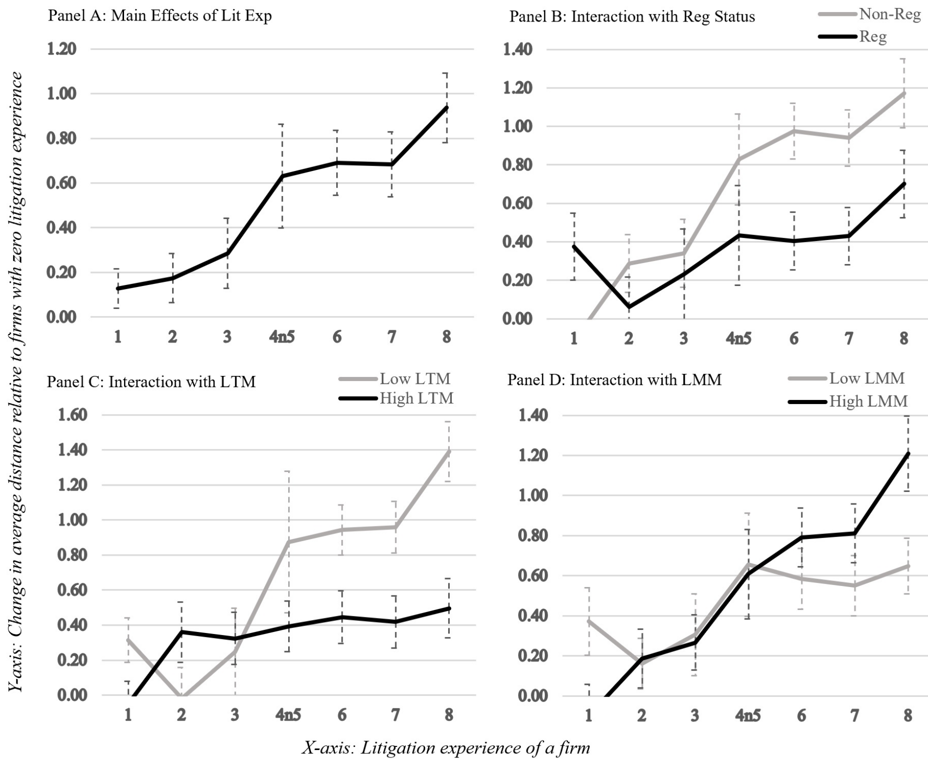

Figure A2: Main and interaction effects of [categorical] litigation experience on distance of competing trademarks

Notes: We illustrate the coefficients of [categorical] litigation experience and its interaction with registration status, lucrativeness of trademarks and molecule submarkets reported in Appendix Table A9. The X-axis represents the non-zero litigation experience of a firm. The Y-axis represents the change in the average distance of competing trademarks relative to firms with zero litigation experience. It is calculated by taking the difference between the estimated average distance of competing trademarks for firms with non-zero litigation experience and firms with zero litigation experience. For instance, in Panel A, the coordinate of one in the x-axis represents the change in average distance of competing trademarks of 0.1249 (about 1 letter) for firms with one litigation experience relative to those with zero litigation experience. Thus, a value greater than zero indicates that the competitors name their trademarks differently in comparison to the incumbents' trademarks. From the graphs, it is evident that as firms develop a reputation for being tough litigants causes competitors to name their trademarks differently; in addition, this deterrence effect is more prominent for its trademarks in high lucrative markets (see Panel D). The dashed bars represent the standard errors clustered at the firm level. Lit Exp, Non-Reg, Reg, LTM, and LMM represent litigation experience, non-registered and registered trademarks, lucrativeness of trademarks, and molecule submarkets, respectively.

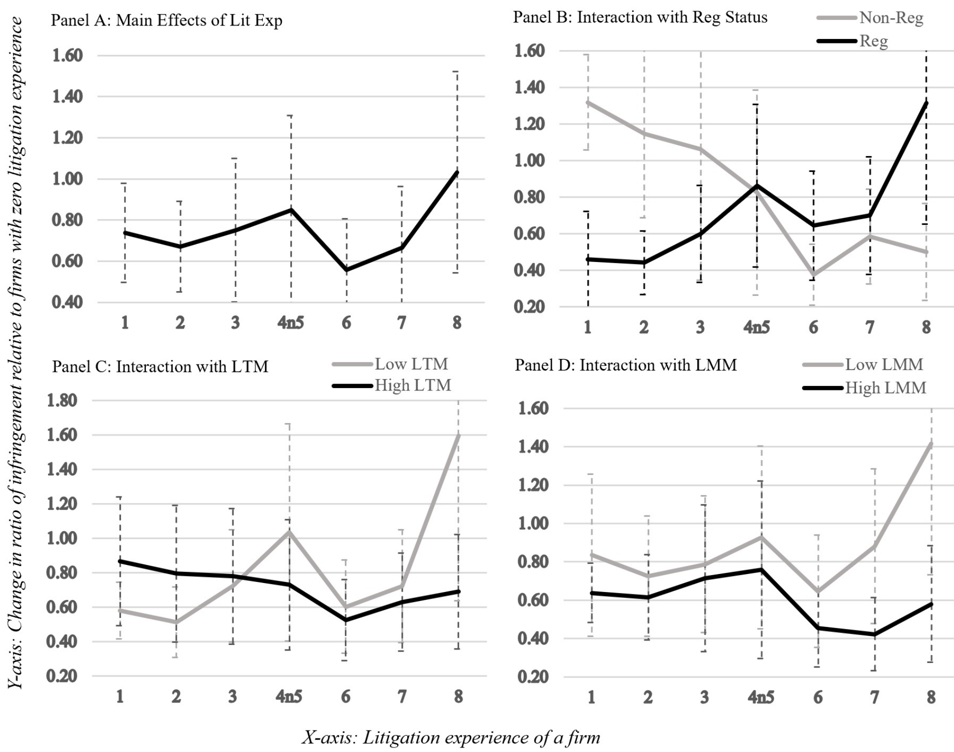

Figure A3: Main and interaction effects of [categorical] litigation experience on number of infringing trademarks

Notes: We illustrate the incidence ratio of [categorical] litigation experience and its interaction with registration status, lucrativeness of trademarks and molecule submarkets reported in Appendix Table A14. The X-axis represents the litigation experience of a firm. The Y-axis represents the estimated change in the risk of infringement for firms with non-zero litigation experience to those with zero litigation experience. It is calculated by estimating the average number of infringing trademarks faced by a firm with non-zero litigation experience and dividing it by the average number of infringing trademarks faced by a firm with zero litigation experience. For instance, in Panel A, the coordinate of one in the x-axis represents the estimated ratio of 0.7372 – meaning a 30 percent reduction in its trademark being infringed for firms with one litigation experience relative to those with zero litigation experience. Thus, a value greater than one indicates a greater risk of being infringed relative to firms with zero litigation experience; whereas a value lower than one indicates a lower risk of being infringed relative to firms with zero litigation experience. From the graphs, it is evident that the firm's reputation of being a tough litigant provides a deterrence effect for its trademark in the high lucrative markets. The dashed bars represent the standard errors clustered at the firm level. Lit Exp, Non-Reg, Reg, LTM, and LMM represent litigation experience, non-registered and registered trademarks, lucrativeness of trademarks and molecule submarkets, respectively.

Silence of the Lambs: The Effects of Misconduct on Entrepreneurial Venture Outcomes

Shreekanth Mahendiran[1]

[1]HEC Lausanne

Abstract

This paper investigates the impact of misconduct allegations on the financing and exit opportunities of entrepreneurial ventures that are technologically related to the perpetrators. To do so, we make use of reported misconduct allegations involving US startups during 1998-2020 to identify our treatment and control group. Employing a stacked difference-in-difference estimation strategy, we find that innocent startups developing similar technologies as the perpetrators are less likely to obtain financing and raise smaller amounts after the misconduct allegations are reported in the news, relative to those developing dissimilar technologies located outside the perpetrators state. The strongest negative effects of these allegation are found to be associated with technological misconduct and sexual harassment, followed by financial fraud, while intellectual property infringements have statistically insignificant impact. Startups related to misconduct perpetrators are no less likely to be acquired than unrelated startups.

Keywords : Entrepreneurship, Misconduct, Venture Capital, Acquistions

1 Introduction

A central concern for entrepreneurs and investors is to manage the fluctuations in access to financing opportunities which disproportionately affect healthy and innovative startups (Nanda & Rhodes-Kropf ,2017). Despite steady increase in investments by investors (Lerner & Nanda ,2020), access to external finance is subject to ebbs and flows of the market conditions (Nanda & Rhodes-Kropf ,2013; Townsend ,2015). Extant literature has highlighted the role of technological revolutions, institutional structures, and government in stimulating financing opportunities (Ewens & Farre-Mensa ,2020; Ewens, Nanda, & Rhodes-Kropf ,2018; P. Gompers, Kovner, Lerner, & Scharfstein ,2008; Howell ,2017; Lerner & Kortum ,2000). Another stream has presented evidence on the impact of external shocks, such as dotcom and financial crisis, in shifting financing and innovative outcomes of startups (Conti, Dass, Di Lorenzo, & Graham ,2019; Howell, Lerner, Nanda, & Townsend ,2020).

However, there has been a surge in misconduct allegations involving entrepreneurial ventures in recent years. Despite these episodes being allegations, therefore not proven misconduct, they could propagate idiosyncratic risks affecting financing opportunities of innocent startups. Consider the recent collapse of FTX after a very public allegations by a competitor – Binance.[1] This has destroyed confidence[2] and brought upon drastic reduction in investments by VC's in the cryptocurrency market from "$6.12 billion in the first quarter of 2022 to just $870 million in the same quarter in 2023".[3] It has also unleashed public ire over the role of politicians and regulators in governing the new financial technology.[4] This is not a standalone episode as the widespread consequences of Theranos collapse had raised questions about the policymakers' role in protecting the welfare of investors and final consumers.[5]

This anecdotal evidence is indicative of the importance for innocent entrepreneurs and investors to understand the consequences of misconduct allegations against a startup; in order, to develop measures to manage it robustly. Consequently, this paper examines the crucial question: Do episodes of misconduct allegation have tangible effects on the outcomes of other innocent startups in the same sector as the perpetrator? And if so, which startups and outcomes are likely to be impacted?

The relationship that we should expect is not a priori clear. The effects of an episode of a misconduct

[1] https://www.reuters.com/technology/ftxs-founder-dismisses-balance-sheet-concerns-false-rumors-2022-11-07/ - Accessed as on October 10th, 2023

[2] https://www.forbes.com/sites/lawrencewintermeyer/2022/12/03/polyamory-denial-and-recriminations-rebuilding-trust-in-crypto-after-ftx/ - Accesses as on October 10th, 2023

[3] https://www.reuters.com/technology/crypto-market-still-bears-scars-ftxs-collapse-2023-10-03/ - Accessed as on October 10th, 2023

[4] https://www.politico.com/news/magazine/2022/12/09/crypto-scandal-sam-bankman-fried-ftx-00073178 - Accessed as on October 10th, 2023

[5] https://www.bloomberg.com/opinion/articles/2018-06-18/theranos-didn-t-just-harm-investors - Accessed as on October 10th, 2023

allegation against a startup (perpetrator hereon) may propagate and generate negative consequences for other innocent ventures if investors and acquirers infer from this kind of event that an entire technological area or entrepreneurial cluster may be "tainted" and prone to similar offenses. For instance: several press accounts have argued that the fall of Theranos has negatively impacted other startups as it had highlighted not only the difficulties in development and commercialization of the underlying technology, in addition to the "hype" culture prevalent in Silicon Valley.[6] On the other hand, competitive dynamics among investors may, at the minimum, not deter their investment strategies (Khanna & Mathews ,2022), especially since investors could attribute allegations as an essential feature of experimentation and/or intrinsic to a particular startup.[7]

To shed light on our questions, we gathered information on 86 episodes of misconduct allegations against startups situated in USA during the 1998-2020 period. We collected this information by searching for all the articles with a select set of keywords from LexisNexis. We use Crunchbase dataset on entrepreneurial ventures to identify the misconduct perpetrators and technologies developed by them. This allows us to identify the treatment group defined as those other innocent startups developing similar technologies and founded at around the time as of the perpetrators' inception. Our control group is defined as those other innocent startups developing dissimilar technologies, located in a different state, and founded at around the time of the perpetrators' inception.

While misconducts are endogenous to their perpetrator, the timing of the allegations being reported in the news would be an exogenous event to other innocent startups. This allows us to estimate the causal effects of misconduct allegations by adopting a stacked difference-in-difference model that evaluates the change in performances of treatment and control groups before and after a misconduct allegation is reported in the news for the first time. In the full model, we incorporate fixed effects such as sector-by-year and state-by-year to control for any time-varying sector and location-specific trends. We include the startup's age and add startup-level fixed effects to absorb any time-invariant heterogeneity.

Our findings reveal that innocent startups developing similar technologies as a perpetrator are 2.66 percent less likely to receive funding after a misconduct event is reported in the news, equivalent to an effect size of negative 11 percent. Additionally, they raise 31 percent fewer funds. Event studies reveal that, reassuringly, there are no significant pre-trends. Our evidence suggests that misconduct events exert negative effects from the year of first occurrence in the news and these effects are persistent as they remain statistically significant in the following five years.

[6] Refer, for instance, to `https://californianewstimes.com/silicon-valley-still-believes-in-promise-of-easy-bloodtests-despite-theranos-scandal/512026/`

[7] `https://www.bloomberg.com/opinion/articles/2022-11-11/ftx-collapse-is-a-feature-not-a-bug-of-financial-innovation` - Accessed on October 10th, 2023

We further show that geographical proximity of innocent startups to a perpetrator is not a crucial channel through which misconduct effects propagate. More interestingly, we find that there is heterogeneity in effects across different types of misconduct. Episodes related to technological misconduct and sexual harassment display similar and statistically significant negative effects, followed by financial fraud, on startup financing outcome, whereas the impact of intellectual property infringements is found to be not significant. This is a remarkable result as it shows that misconduct episodes not only cast doubt on the technologies of innocent startups, but also on their modus operandi.

Going beyond these initial findings, we delve into the responsiveness of venture capitalists (VCs hereon) and experienced investors, proxied by their investment in particular sector, to misconduct allegations. Surprisingly, we find that VCs and investors with a successful track record are relatively less responsive to these misconduct allegations. Specifically, we find that the likelihood that treatment startup attracts venture capital (VC) and the amount raised declines by 1 percentage point and 16 percent, respectively, after the misconduct allegations are reported in the news. We obtain similar effects when we examine the likelihood of obtaining financing from successful VCs and amount raised from these financing sources. Taken together, these results suggest that misconduct allegations exert stronger negative effects on those investors that have relatively lower screening and monitoring skills and may suffer the largest reputation costs if their investees turn out to be misconduct perpetrators.

We also investigate whether the negative effects of an initial misconduct allegation also affect a startup's exit – IPO and acquisitions – opportunities. We show that startups developing similar technologies are as likely as startups developing dissimilar technologies to achieve a successful exit after the misconduct allegation is reported.

This study contributes to several strands of literature. Firstly, we add to the theoretical development by Grenadier, Malenko, & Strebulaev ,2014, and Nanda & Rhodes-Kropf ,2017, by bringing to fore that relevance condition plays a significant role in manifestation of the negative effects on innocent startups. Further, negative effects are moderated by the expectation about manageability of risk raised by misconduct allegations – as investors want to protect their reputation of being reliable and guiding the startups through challenging periods.

Our work expands upon the extensive research on corporate frauds and scandals by examining how misconduct allegations affect the performance outcomes of entrepreneurial ventures (Cumming, Dannhauser, & Johan ,2015). This literature has focused on the characteristics of firms involved in frauds (Burns & Kedia ,2006; Efendi, Srivastava, & Swanson ,2007), factors predicting fraud (Dimmock & Gerken ,2012; Parsons, Sulaeman, & Titman ,2018) and the mechanisms for detecting it (Dyck, Morse, & Zingales ,2010), effects of corporate frauds on household stock market participation and investment advisers (Giannetti & Wang ,2016; Gurun, Stoffman, & Yonker ,2018), and penalties paid by managers responsible for corporate misconduct and by outside directors of sued firms (Fich & Shivdasani ,2007; Karpoff, Lee, & Martin ,2008). Relative to these studies, our focus is on how misconduct allegations affect the performance outcomes of entrepreneurial ventures. The performance of these nascent firms crucially depends on the financial and non-financial capital of their investors (Bernstein, Giroud, & Townsend ,2016; Bottazzi, Da Rin, & Hellmann ,2008; Hellmann & Puri ,2002; Lerner ,2000; Sørensen ,2007), but attracting this form of capital is hampered by information frictions inherent in investor-startup relationship (Bottazzi, Da Rin, & Hellmann ,2016; Conti, Thursby, & Rothaermel ,2013; P. A. Gompers ,2022; Howell ,2020; Hsu ,2004). Motivated by this evidence, our study shows that misconduct allegations have profound negative effects on the ability of innocent startups to raise investments, especially from investors that are relatively less experienced in screening and monitoring their investments. In addition to being strong, these effects span a large spectrum of misconduct allegations and are persistent over time.

Our paper also contributes to the extant literature on how negative shocks propagate across entrepreneurial ventures (Conti et al. ,2019; Townsend ,2015). While these studies have investigated the effect of common shocks, our focus is on the negative externalities misconduct allegations produce. We also address the literature exploring the opportunistic behavior by investors to protect their reputation and fund-raising opportunities (Chakraborty & Ewens ,2018; Jelic, Zhou, & Ahmad ,2021). Our empirical evidence reveals that the strategic behavior of investors taking advantage of misconduct allegations not only results in the spillover effect of misconduct allegations to innocent startups but also perpetuates the negative effect for a longer period.

Finally, we contribute to the literature on guilty by association owing to corporate misconduct (Naumovska & Zajac ,2022; Paruchuri & Misangyi ,2015) in several ways. We extend the literature by situating our study in the entrepreneurial landscape where we also highlight the role of ex-ante uncertainty in propagating the negative effects of misconduct allegations. While this literature has identified stigmatization as one of the primary mechanisms of the spillover effect, we bring attention to the potential strategic behavior of investors at times of negative events. We also address the gap in this literature by providing evidence on heterogeneous negative effects by different types of misconduct allegations. In addition, we distinguish investors based on their endowments and prominence to highlight the differences in their investment decision-making after a misconduct allegation is revealed.

This paper proceeds as follows: Section 2 presenting theoretical predictions that integrate insights from entrepreneurship and organization theory. Section 3 details the steps undertaken to identify misconduct allegations and construct our dataset sourced from Crunchbase, which allows for empirical testing of our theoretical predictions. Next, we provide descriptive statistics of our sample followed by describing our primary empirical approach and presentation of the results, along with an exploration of the mechanism. We conclude by discussing the implications of our work and outlining potential avenues for future research.

2 Theoretical Framework

We develop our hypotheses building upon extant literature that considers the experimentation approach adopted by investors towards entrepreneurship and its implications on their investment behavior (Kerr, Nanda, & Rhodes-Kropf ,2014; Manso ,2016; Nanda & Rhodes-Kropf ,2017). We begin with the framework in which startups operate under uncertainty and aim to maximize the tradeoff between financing risk and exit outcomes. To achieve this, startups seek investment to overcome hurdles, achieve milestones and attain successful exit outcomes in the market. On the other hand, investors face extreme uncertainty which they tackle by relying upon available information to evaluate the potential success of a startup. Consequently, investors make sequential investment decisions to maximize the trade-off between expected payoff and option to abandon their investment if a startup fails to achieve interim milestones (Bergemann, Hege, & Peng ,2009; P. A. Gompers & Lerner ,1995; Nanda & Rhodes-Kropf ,2017).

Two types of information influence the investor's decision-making process both in the initial and continuation with subsequent investments. First, publicly observable information shapes the investor's expectation on whether other investors will be interested in investing in future rounds. Positive public information reduces financing risk and real option value thereby increasing demand in the startup from future investors. Conversely, negative public information amplifies financing risk and real option value as investors would anticipate diminished demand for the startup in the future. Therefore, publicly observable information plays a pivotal role in influencing investment decisions of investors. On the other hand, investors must make investments to gain access to the private information that constitutes (a) underlying fundamentals such as technological/project novelty, new market linkages etc., (b) capabilities of the founding team, and (c) technological uncertainty, market risk and so on.

In this research, the publicly observable information refers to misconduct allegations being reported in the news for the first time. A critical assumption here is that perpetrators strategically delay the sharing of information, particularly about failures or any negative events, to continue to secure funding from potential investors. Consequently, we assume that there is no strategic motives by internal or external stakeholders to make such misconduct allegations more visible in public forums, such as newspaper articles. This implies that there is no specific selectivity in the visibility of a particular type of misconduct allegation throughout the years.[8]

These allegations may require investors to employ their resources to verify such claims and validate the credibility of the allegations. Additionally, investors may incur additional costs in implementing monitoring measures to ensure that startups facing misconduct allegations can achieve their pre-determined goals. However, a pertinent question arises – could these misconduct allegations have spillover effects, influencing investors' expectations about other innocent startups and impacting their future financing and exit opportunities? If so, whether the spillover affects any innocent startup or only those that share certain characteristics with the perpetrator.

Beginning with the first question, our context is the startup ecosystem which is fraught with extreme uncertainty regarding the financing and exit outcomes, as well as underlying factors such as founding team capabilities, technology, product development and commercialization process (Colombo ,2021). Further, investors must deal with uncertainty over how startups will respond to favorable (unfavorable) events, say new technology (misconduct allegation) (McMullen & Shepherd ,2006). In the presence of extreme uncertainty, investors rely greatly upon subjective judgements concerning factors such as top management team (Higgins & Gulati ,2006), human capital (Nagy, Pollack, Rutherford, & Lohrke ,2012), passion (Chen, Yao, & Kotha ,2009), entrepreneur's willingness to learn and adapt (Ciuchta, Letwin, Stevenson, McMahon, & Huvaj ,2018), network with prominent investors (Hsu & Ziedonis ,2013), and others, relative to objective judgements based on market-related factors (Huang & Pearce ,2015; Kirsch, Goldfarb, & Gera ,2009).

The substantial body of work in organizational misconduct literature reveals existence of *stigma (negative)* effect of adverse information (such as financial misconduct) on innocent firms belonging to the same industry as the perpetrators (B. Baker, Derfler-Rozin, Pitesa, & Johnson ,2019; Bruyaka, Philippe, & Castañer ,2018; Paruchuri & Misangyi ,2015; Yin, Cheng, Yang, & Palmon ,2021; Yue, Rao, & Ingram ,2013). Applying this evidence for established firms to our context, we expect any negative information, such as misconduct allegations, to increase uncertainty for investors and adversely affect their expectation about the potential success of innocent startups in subsequent periods.

The underlying mechanism is that these allegations evoke a change in investors' perceptions where

[8]Obviously, we do not capture the entire set of misconduct allegations, but most likely those have generated sufficient interest among interested stakeholders such as investors, entrepreneurs, regulators, and others. We tackle this by verifying whether the outcomes change by the changes in the public interest, proxied by the number of newspaper articles covering each misconduct allegation. The results do not offer any support to such intuition.

they tend to suspect similar illegitimate practices to be abound in innocent startups (Jonsson, Greve, & Fujiwara-Greve ,2009). In addition, extant literature underscores the significance of reputational loss in motivating the investors to reduce their association with innocent, yet stigmatized, startups (Jensen ,2006; Jonsson et al. ,2009). It increases the risk profile of these innocent, yet stigmatized, startups thereby affecting its expected valuation by investors. Investors may also expect such stigmatization to be leveraged by future investors to negotiate favorable deals demanding a greater equity stake at a discounted rate. This potential for higher dilution of investors' equity stake in future rounds reduces their expected payoff. Consequently, a misconduct allegation will significantly lower the attractiveness of innocent startups for future investments. This may induce the investors to act conservatively either by abstaining from participating in financing rounds or investing lower amounts to gain additional information to resolve uncertainty surrounding the innocent startups (Nanda & Rhodes-Kropf ,2017).

Till now, our proposition assumes that the investors' concern for their reputation emanates from being associated with innocent, yet stigmatized, startups as misconduct allegations becomes public knowledge. However, Chakraborty & Ewens ,2018, reveal that investors strategically delay adverse information about their fund performance to protect their reputation and facilitate successful fund-raising. Similarly, it can be argued that investors could strategically time their termination of under-performing startups in such a way that their reputation for sorting and identifying successful ventures is not tainted. This strategic maneuver stems from the recognition that an investor's reputation significantly influences their ability to raise funds from limited partners (Metrick & Yasuda ,2010), syndicate with other co-investors (Plagmann & Lutz ,2019), and attract promising entrepreneurs seeking investments (Chahine, Filatotchev, Bruton, & Wright ,2021; Hsu ,2004; Nahata ,2008).

Grenadier et al. ,2014, develop this idea as a theoretical model to show that investors will adopt a "blending-in" strategy during times of a common shock. The authors theorize that there could be investors who are genuinely affected by the shock resulting in terminations of their ventures. More importantly, the common shock creates favorable conditions for another set of investors who either delay the termination of underperforming ventures or expedite terminations, which includes healthy ventures that might succeed with continued investments. The authors refer to these as *strategic terminations* undertaken by investors as the shock event occurs to safeguard their reputation rather than continuing to invest and terminate in normal times which might invite reputational penalties. In sum, a common shock can lead to a more pronounced negative effect to manifest in the economy.

Further, the authors theorize a strategic game being played between two types of investors – high and low – to obscure their true type to the external stakeholders. It could be expected that the low-type investors terminate ventures to avoid incurring reputational loss as the shock event occurs. Consequently, high-type investors would prefer to adopt a separating strategy where they want to distinguish themselves from the low-type investors thereby inducing them to delay termination of their ventures. Anticipating this, low-type investors would delay their terminations as well thereby attempting to blend in with the high-type investors and obscure their true type to the external stakeholders. Therefore, this dynamic results in the negative effects of strategic termination perpetuating for a longer period.

Unlike a common shock, as theorized in Grenadier et al. ,2014, an idiosyncratic shock such as misconduct allegations would not allow all investors to adopt the “blending-in” strategy. As previously argued, these allegations provide negative information relevant only to innocent startups that share characteristics with the perpetrators. Thus, investors investing in innocent startups that meet the *relevance condition* have the capacity to successfully undertake terminations when these allegations are reported in the news for the first time.[9]

Paruchuri & Misangyi ,2015; Zuckerman ,2000, 2012, argue that investors identify similarities based on certain characteristics to categorize firms into specific groups (e.g., technology-specific groups such as cryptocurrency, AI and, internet-of-things, or sector-specific groups such as biotechnology, analytics, and transportation). In accordance with this, extant literature provides us with certain characteristics namely: (a) industry (Que & Zhang ,2021), (b) technology (Conti et al. ,2013), (c) geographic locations (Stuart & Sorenson ,2003), (d) founder characteristics (Hsu ,2007) and others that VCs use to evaluate startups for financing opportunities.

Naumovska & Zajac ,2022, posit investors are inclined to attribute misconduct more strongly to innocent firms when there is a greater similarity with the perpetrator in terms of specific and nuanced characteristics. Further, Paruchuri & Misangyi ,2015, argue that a higher degree of similarity between perpetrator and innocent startups based on a particular characteristic will facilitate transmission of culpability from perpetrator to innocent startups – referred to as *generalization-instantiation* process. This generalization process appears to be true for startups as anecdotal evidence indicates that sophisticated investors, such as VCs, do make use of fine-grained categories to assign culpability to innocent startups. For instance, the recent collapse of FTX, followed by Binance, resulted in loss of confidence among investors towards startups developing products based on cryptocurrency technology.[10] But this did not spillover to startups developing technologies related to other digital financial products.

[9] If investors do not adhere to the relevance condition, then there is a greater chance of revealing their true type or even being inferred as a low type. This will affect their fund-raising and investment opportunities in the future.

[10] Refer to the following articles:`https://www.cnbc.com/2022/12/19/three-ways-the-ftx-disaster-will-reshape-crypto.html`;`https://edition.cnn.com/2022/11/11/investing/ftx-crypto-consequences-lehman/index.html`;`https://fortune.com/2023/04/15/bitcoin-rebounds-but-crypto-industry-tepid-investors-wait-and-see/` - Accessed as on June 23rd, 2023.

Therefore, we hypothesize that when misconduct allegations become public knowledge, investors' perceptions of innocent startups developing similar technology as the perpetrator will be affected.[11][12] Based on these considerations, we propose the following baseline hypotheses:

Hypothesis 1a: Innocent startups developing similar technology, as the perpetrator, will face lower probability of obtaining a financing round, relative to those developing dissimilar technologies and located in a different state.

Hypothesis 1b: Innocent startups developing similar technology, as the perpetrator, will raise lower amount of investment, relative to those developing dissimilar technologies and located in a different state.

We have postulated that investors leverage technology-specific categories to draw similarities between the perpetrator and innocent startups. However, another characteristic that warrants exploration within the context of the *relevance condition* is the geographic location similarity between the perpetrator and innocent startups. Over the past two decades, newspaper articles have extensively documented the "fake it till you make it" culture emanating from Silicon Valley. While initially portrayed positively as a culture that fosters radical innovation and novel market linkages, recent events, including misconduct cases involving Theranos, WeWork, Uber, and FTX[13] have brought to light negative connotations associated with this culture, such as toxic work environments, irrational exuberance, fraudulent financial practices, misleading technological claims, and other unethical behaviors.

Building on insights from Naumovska & Zajac ,2022, who propose a concept known as deductive generalization, we argue that startups causally associated with a negative stereotype will experience a pronounced negative effect as a misconduct allegation is revealed. Investors could causally associate misconducts with culture emanating from a particular geographic origin. Consequently, investors may

[11] Note that we do not dispute that generalization-instantiation process may apply to other identity categorization such as race, gender, origin, and so on. Rather, we expect that investors perception about innocent startups that share technology-specific characteristics with the perpetrators will alter the most owing to a misconduct allegation, relative to other identities.

[12] Krieger ,2021; Naumovska & Lavie ,2021, propose the presence of competition (positive) effect owing to adverse information (such as failure, misconduct etc.,) on the innocent firms. The underlying mechanism hinges on the nature of competitive dynamics prevailing in the industry. In similar vein, it can be argued that competition among investors can result in choosing to invest in these innocent startups choosing to levy higher weightage on the opportunities of innovative ventures. Khanna & Mathews ,2022, theorize that non-established investors are likely to take higher risks to be associated with successful exit outcomes in the future, thereby develop a reputation of successful investor. While this presents an argument for opposing effect, we make the same assumption as Nanda & Rhodes-Kropf ,2017, that investors' forecasts are correct in expectation. This means that investors can correctly predict the investment behavior of other potential investors in the future. If investors today expect negative reaction to misconduct allegations, then it will not be rational for other potential investors to invest in the future. Additionally, we expect the combined negative effect through stigmatization and investors strategically terminating under the guise of a misconduct allegation would prevail over any positive effect for innocent startups that develop similar technology as the perpetrators.

[13] `https://www.forbes.com/sites/dileeprao/2021/09/15/fake-it-till-you-make-it-is-this-one-more-lie-from-silicon-valley-like-theranos/`;`https://www.wired.com/story/theranos-and-silicon-valleys-fake-it-till-you-make-it-culture/`;`https://www.theguardian.com/technology/2022/jan/04/elizabeth-holmes-verdict-analysis`;`https://stanfordreview.org/lets-put-the-brakes-on-fake-it-till-you-make-it/` - Accessed on June 28th, 2023.

generalize these illegitimate practices to innocent startups belonging to the same origin as the perpetrators. This generalization, in turn, has the potential to curtail the financing opportunities of innocent startups sharing a geographical origin as the perpetrator. This provides us with our next hypothesis.

Hypothesis 2a: Innocent startups that are geographically proximate to the perpetrator will face lower probability of obtaining a financing round, relative to those that are not geographically proximate and developing dissimilar technology.

Hypothesis 2b: Innocent startups that are geographically proximate to the perpetrator will raise a lower amount of investment, relative to those that are not geographically proximate and developing dissimilar technology.

Our previous discussion delved into the distinct strategies adopted by two kinds of investors – namely high and low – in timing their termination of innocent startups. It underpins the innate tendency of investors to develop a reputation of being able to identify successful startups. Nevertheless, it overlooks another facet of investor's reputation that hinges upon their ability to leverage financial and non-financial endowments to nurture startups through different stages and achieve a successful exit outcome. This aspect is of paramount importance as startups actively seek out investors who can be relied upon to continue investing in their venture (Khanna & Mathews ,2022). This constitutes investors willingness to manage any unexpected risks that arise when a misconduct allegation becomes public knowledge, thereby affecting the prospects of innocent startups.

It is crucial to recognize that misconduct allegations encompass a wide spectrum of transgressions – ranging from intellectual property infringements to sexual harassments –injecting varying degrees of risks and, accordingly, affecting the investors' reactions towards the innocent startups. Investors aim to develop a reputation for managing various risks effectively, therefore must contend with the expectations of external stakeholders. We expect external stakeholders to hold rational expectations about the manageability of risks associated with different types of misconduct allegations. These expectations depend upon their determination of an investor's ability to verify whether other innocent startups are prone to similar practices as the misconduct allegations. Further, it involves the investors to be able to forecast the potential outcomes, including the spillover effect, and costs involved in implementing any mitigation measures to address the challenges presented by misconduct allegations. We posit that misconduct allegations meeting verifiability and evaluation criteria raise manageable risks, while those failing to meet these criteria engender unmanageable risks. Consequently, we propose that the investors' response to different types of misconduct allegations can exhibit variation in both direction and magnitude, contingent upon the expectations concerning the manageability of risks.

Expanding upon this premise, we suggest that misconduct allegations such as intellectual property infringement raise manageable risks. It is important to note that these types of misconduct allegations typically occur during the later stages of startup's life-cycle – when it has completed the development stage and is entering the commercialization phase. It is highly probable that investors can avail sufficient information to assess whether other innocent startups developing similar technology as the perpetrator are culpable of similar transgressions. Even if that is the case, these investors can employ their resources to identify solutions to mitigate such transgressions. Furthermore, investors who persevere through such challenging periods and provide invaluable resources stand to reap a substantial reputational dividend. This esteemed reputation signifies their willingness to manage any unexpected risks that may arise throughout a startup's multi-faceted lifecycle. Consequently, it facilitates external stakeholders to develop expectation that these investors belong to the high type who can identify promising startups and willing to nurture it to attain a successful exit outcome. Conversely, investors who opt for termination run the risk of developing a reputation as a low type. Anticipating this, even the low-type investors can decide to adopt a pooling strategy, continuing their investments in other innocent startups, to obscure their true type. Therefore, we expect that misconduct allegations posing manageable risks will have minimum or no impact on the financing opportunities of innocent startups developing similar technology as the perpetrators.

On the other hand, we suggest that misconduct allegations such as sexual harassment introduce unmanageable risks. It is essential to acknowledge that confidently assessing whether other innocent startups engage in similar practices is challenging. The potential for information asymmetry also plays a role here, as investors could suspect innocent startups to conceal any illegitimate practices to secure future investments. In addition, investors may not be able to quantify the potential outcome of such allegations, and the extent of reputational loss resulting from association with stigmatized startups. This heightens uncertainty for investors which in turn affects the prospects of innocent, yet stigmatized, startups. In combination, it creates conditions for investors to lower their expectations about the potential success of innocent startups, in addition to empowering those who want to undertake strategic terminations under the guise of such misconduct allegations. Therefore, we expect misconduct allegations giving rise to unmanageable risks will exert a substantial negative impact on the financing opportunities of innocent startups developing similar technology as the perpetrators.

We propose the following hypothesis based on the above-stated considerations.

Hypothesis 3: Misconduct allegations that instigate expectation of unmanageable risks will have a greater negative effect on technologically similar innocent startups, relative to those of manageable *risks.*

A necessary condition for our earlier hypotheses is the role of ex-ante uncertainty in influencing the expected payoff of investors as a misconduct allegation is reported. From previous studies, (Bloom, Bond, & Van Reenen ,2007; Julio & Yook ,2012; Nanda & Rhodes-Kropf ,2017), we elicit that level of uncertainty is proportional to financing risk and real options value. In other words, increase (decrease) in uncertainty results in higher (lower) financing risk and real options value of startups, thereby reducing (increasing) expected payoff of investors. This may induce investors to act more cautiously (expeditiously) in investment decisions as an event triggers an increase (decrease) in uncertainty.

Given this, we explore whether a change in uncertainty does play a significant role in altering the investors' perceptions and creating negative effect for innocent startups sharing similar characteristics, as the perpetrators, after a misconduct allegation is reported. The relationship between misconduct allegations and change in investors' perceptions, thereby change in expected payoff, under different ex-ante levels of uncertainty is represented in Appendix Figure 1. In our context, we know that early-stage startups face extreme and multi-dimensional uncertainty. As argued earlier, a misconduct allegation would introduce additional uncertainty that investors must resolve while considering an investment decision. This would result in a greater negative effect on innocent startups sharing characteristics with the perpetrator. On the other hand, investors possess much more information about the late-stage startups thereby face less uncertainty. We expect that this ex-ante low level of uncertainty dissipates any negative effect caused by a misconduct allegation.

Hypothesis 4: A misconduct allegation will result in significant (negligible) negative effect on early-stage (late-stage) innocent startups developing similar technology, as the perpetrator, relative to those developing dissimilar technology and located in a different state.

Finally, it is crucial to investigate whether misconduct allegations affect the exit opportunities of innocent startups developing similar technology as the perpetrator. As explained in Hypothesis 1a and 1b, misconduct allegations increase the financing risk for these innocent startups, thereby reducing their outside option and diminishing their bargaining position (Nanda & Rhodes-Kropf ,2017). Further, potential acquirers or partners may suspect the exit opportunities through several channels: they may suspect similar illegitimate practices to be abound in these innocent startups, leading to suspicion over their credibility. Second, potential acquirers or partners may fear absorbing reputational damage which could be generalized from the perpetrator to these innocent startups by external stakeholders, thereby incurring the cost of reputational loss themselves. Third, these misconduct allegations could attract more scrutiny from regulatory authorities over any potential acquisition. This could induce potential acquirers to fear a lengthy acquisition process and incur additional associated costs to overcome the challenges presented by the misconduct allegations. This will reduce the expected gain for the potential acquirer by undertaking acquisitions of these innocent startups. All these factors can collectively contribute to reducing the prospect of these startups achieving a successful exit outcome.

Hypothesis 5: Innocent startups developing similar technology, as the perpetrator, will experience lower likelihood of attaining an exit outcome, relative to those developing dissimilar technology and located in a different state.

3 Data and Sample Construction

We combine data on US startups and their investors, which are available on Crunchbase, with information on misconduct allegations collected from LexisNexis. In this section, we describe the process to collect misconduct allegations which were then mapped to Crunchbase database to identify the misconduct perpetrators, treatment, and control group.

3.1 Identification of startup misconduct allegations

We access LexisNexis to collect entire set of misconduct allegations against US startups that were reported in newspapers and legal briefs during the period between 1998 and 2020. To do so, we employed the combination of the following search terms: (a) startup and lawsuit; (b) startup and allegation news; (c) startup and economic espionage; (d) startup and fraud; (e) startup and fraudulent; (f) startup and harassment; (g) startup and infringement; and (h) startup and scandal. This search provided us with 572 newspaper articles and legal briefs documenting misconduct allegations by US startups. These articles were manually checked by a research assistant and then by the author to identify unique cases. This screening process yielded a sample of 135 unique cases for which we have information regarding the startup's perpetrator's name, timing, and type of misconduct allegations.

3.2 Mapping the startup misconduct allegations to Crunchbase

We linked this information from LexisNexis with the startup dataset available from Crunchbase. Crunchbase is an online directory that records fine-grained information on startups, their founders, and investors. As described by Conti & Roche ,2021; Te et al. ,2023, a significant portion of the data is entered by Crunchbase staff, and the remaining information is filled-in through crowdsource. Registered members can enter information to the database, which is reviewed then by the Crunchbase staff. Relative to directories such as VentureXpert and VentureSource, Crunchbase has the advantage of providing a broader coverage of startups since it also includes those that did not raise any venture capital. We employed the startup names reported in the articles and legal briefs available from LexisNexis. This resulted in successfully identifying 86 perpetrators – startups against which misconduct allegations are raised – in the Crunchbase dataset.

3.3 Classification of misconduct allegations by risk manageability criteria

The details available from the retained articles allow us to generate five mutually exclusive misconduct categories namely: (a) technological misconduct; (b) intellectual property infringements; (c) financial fraud; (d) sexual harassment; and (e) other unethical business practices. This classification was undertaken based on the allegation described in the first news coverage. We provide below a definition of these misconduct categories:

- *Intellectual property infringements*: This category encompasses allegations where a startup had allegedly participated in the stealing of trade secrets from a rival, or infringed its intellectual property rights deriving from patents, trademarks, and copyrights. As an example, the 1999 Recording Industry Group lawsuit against Napster for alleged copyright infringement and music privacy was included under this category.[14]

- *Financial fraud*: This category includes allegations where a startup had committed securities fraud, misreporting of financial details to attract investments, and diversion of funds for activities including personal splurges. For instance, in 2017, investors sued their investee startup Tezos alleging that its initial coin offering was an unregistered, and therefore illegal, securities offering.[15]

- *Sexual harassment*: This category includes allegations of harassment ranging from inappropriate behavior to sexual torture carried out by either a manager or a co-worker. For instance, in 2014, Business Insider reported several cases of sexual harassment experienced by female employees at Zillow. The article described the company culture as one of an "adult frat house" and female employees were fired for refusing sexual advances from co-workers.[16]

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[14]"Recording Industry Group sues Napster, alleging copyright infringement on net", The Wall Street Journal, 1999. [https://www.wsj.com/articles/SB944711263509285168 – Accessed on October 7th, 2021].

[15]"Tezos ICO falls from grace as lawsuit gets filed," The Street, 2017 [https://www.thestreet.com/markets/currencies/tezos-ico-falls-from-grace-as-lawsuit-filed-14380889 – Accessed on October 7th, 2021].

[16]"Lawsuit against Zillow accuses company of 'Sexual Torture' of female employees", Business Insider, 2014 [https://www.businessinsider.com/sexual-harassment-suit-against-zillow-2014-12 – Accessed on October 7th, 2021].

- *Technological misconduct*: This category comprises allegations where a startup made false claims about its technology or attempted to introduce a novel technology without authorization from authorities. As an example, this category includes the famous case of Theranos, where its founders misled everyone about their blood-testing technology as exposed by a Wall Street Journal article published in 2015.[17]

- *Other unethical business practices*: This is a residual category of misconduct allegations.

Of the 86 misconduct allegations, 40 to intellectual property infringements, 16 to financial fraud, 14 to sexual harassment, 7 were assigned to the category of technological misconduct, and 9 to the residual category. The full list of misconduct allegations is provided in Appendix Table A1 to A5.

We classify the different types of misconduct allegations under *manageable* and *unmanageable risks* based on verifiability and evaluation criteria. To remind, we postulated that external stakeholders' expectations over an investor's ability to verify innocent startups culpability in similar alleged practices and evaluate potential consequences of such misconduct allegations determines risk manageability. Following these criteria, we classify "intellectual property infringements" under *manageable risks* as investors can verify whether their ventures engage in similar infringements and take necessary mitigation measures to overcome this risk, even if their ventures are found culpable. On the other hand, we classify "technological misconduct", "financial fraud", and "sexual harassment" as posing *unmanageable risks*. We argue that these three types of misconduct allegations present significant challenges in terms of accurate verification. Investors may suspect that stigmatized startups may be concealing similar practices to secure future investments. Consequently, investors face the risk of reputation damage by associating with such startups in the future. Moreover, it introduces uncertainty over expected outcomes – costs and benefits – thereby inducing investors to lower their expectations about the potential success of these innocent, yet stigmatized, startups.

3.4 Sample Construction

The objective of our sample construction is to develop a dataset that facilitates stacked difference-in-difference estimation to evaluate the impact of misconduct allegations on the financing and exit market opportunities of innocent startups developing similar technologies as the perpetrator. We follow the process adopted by A. C. Baker, Larcker, & Wang ,2022; Bleiberg ,2021; Cengiz, Dube, Lindner, &

[17]"Hot startup Theranos has struggled with its blood-test technology", The Wall Street Journal, 2015. [https://www.wsj.com/articles/theranos-has-struggled-with-blood-tests-1444881901 – Accessed as on October 7th, 2021].

Zipperer ,2019, with the following steps: (a) creation of individual stack of treatment and control group for each misconduct allegation, and (b) appending the individual stack to create a stacked dataset.

To begin with, we collected information about the establishment year of the 86 startups against which the misconduct allegations were reported. We successively retained all the startups that were established in the interval starting three years before the establishment date of a misconduct perpetrator and ending one year after. By applying this temporal criterion, we ensure that the treated and control startups are at a similar stage in their lifecycle and exposed to similar macroeconomic conditions as the misconduct perpetrators.

In the next stage, we take steps to determine the sets of startups' developing similar and dissimilar technologies as the misconduct perpetrators. To do so, we started with the technology keywords available from Crunchbase. It should be noted that these technology keywords were chosen by the startups when they registered their profile on Crunchbase. Unfortunately, a close inspection of these keywords revealed that they do not always accurately describe the technology developed by a startup. This is because the startups have an incentive to list many different and fashionable technology keywords, such as artificial intelligence, to improve their attractiveness and gain greater visibility to potential investors. To address this concern, we applied a machine learning algorithm to re-assign keywords that would more accurately describe a startup's technology. We operationalize this by considering the entire corpus of technology keywords available from Crunchbase and re-assigned them to the startups depending on whether these keywords -appropriately stemmed- would appear at least once in either startup's description available from Crunchbase or the newspaper articles pulled from LexisNexis. On average, this algorithm assigns eight technology keywords to each startup (s.d: 6). Using these new set of technology keywords, we re-assigned each startup a set of sector groups according to the crosswalk provided by Crunchbase.[18] On average, a startup is described by two sector keywords.

Building on this, we consider these criteria for generating our treatment group that constitutes startups that share the following characteristics with the perpetrator: (a) established around the same period (temporal criterion), and (b) at least one of the most relevant keywords regarding technology, sub-sector, and sector group.[19] Therefore, our treatment group constitutes those innocent startups developing similar technology as the perpetrator.

We consider these criteria for generating our control group that constitutes startups that share the following characteristics with the perpetrator: (a) established around the same period (temporal criterion),

[18]The crosswalk is available at `https://support.crunchbase.com/hc/en-us/articles/360043146954-What-Industriesare-included-in-Crunchbase-`

[19]The relevance of the technology, sub-sector and sector keywords was manually verified by the author.

(b) do not share any of the relevant keywords regarding technology and sub-sector but share at least one sector group, and (c) located in a different state. The final criteria (c) were imposed to ensure that the regression estimates do not suffer from any contamination of the negative effect spill over to innocent startups located in the same state as the perpetrators. Additionally, we ensure that the control group was selected only from sub-sectors in which there were no misconduct allegations reported. Given this, our control group constitutes those innocent startups developing dissimilar technology and located in a different state as the perpetrator.

We make use of the above-stated inclusion criteria for each misconduct allegation to generate our treatment and control group. In all cases, we were able to identify a greater number of startups for the control group relative to the treatment group. We opted for a balanced sample and therefore randomly assigned one control startup – among those eligible[20] - per treated startup. Thus, we were able to generate a balanced individual stack of treatment and control group for each of the 86 misconduct allegations. Finally, we appended these individual stacks to generate a stacked dataset. Our final dataset encompasses 30,812 startups equally split between treatment and control group.

4 Descriptive Statistics

The descriptive statistics for our sample startups during the five-year period before and after the first occurrence of a misconduct allegation in the news is provided in Table 1. We distinguish between innocent startups developing similar technologies as the misconduct perpetrators (Treatment = 1) and those developing dissimilar technologies and located in a different state (Control = 0). To begin with, most of our sample startups belong to the software sector – 47 percent and 56 percent constituting the innocent startups in the treatment and control group, respectively. We can derive from their descriptions from Crunchbase that they claim to be developing new technologies. Much of our treatment group is in the state of California and New York (about 41 percent), whereas only 25 percent of the startups in the control group are established in these two states.

Examining financing opportunities, we observe that the treatment group is much more likely to raise financing round and receive higher investments from investors, on average, during the five-year period prior to the misconduct allegations being reports, relative to those in the control group. However, we find that the likelihood of treatment group obtaining a financing round reduces by 5 percentage points during the five-year period after the misconduct allegations were reported, relative to the control group.

[20] The number of eligible control startups is 62,733.

In addition, the growth in average investment raised from investors per year by the control group is much higher than the treatment group – 15 percent versus 9 percent. The difference in growth rate of investment raised from VCs between the control and treatment group offers a much starker with 13 percent and 4 percent per year, respectively. Overall, these findings indicate that innocent startups developing similar technology as the perpetrators experience greater magnitude of negative consequences of misconduct allegations, relative those developing dissimilar technology and located in different state to the perpetrator. Examining liquidity events, we observe that the treatment group are as likely to experience both acquisition and initial public offering (IPO) as those in the control group.

[Insert Table 1 here]

5 Empirical approach

To examine how a misconduct allegation impact the opportunities of startups developing similar technologies as the misconduct perpetrator, we estimate a stacked difference-in-difference model and compare, over time, the performance outcome of treatment and control startups. Our conjecture is that the effects of a misconduct allegation involving a startup may propagate and generate negative consequences for other innocent startups developing similar technologies (treatment group) relative to those developing dissimilar technologies and located in a different state (control group). We formalize the primary econometric model in Equation (1) given below:

$$Y_{i,j,k,s,t} = \alpha + \beta_1 PostMisconduct_{j,t} + \beta_2 PostMisconduct_{j,t} * Tech.SimilarStartup_{i,j} + \gamma LnAge_{i,t} + \omega_i + \phi_j + \theta_{k,t} + \tau_{s,t} + \epsilon_{i,j,k,s,t} - Equation(1)$$

$Y_{i,j,k,s,t}$ is the performance outcome in year t of startup i associated with the misconduct allegation j developing a technology in sector k located in state s. We consider three performance measures namely: (a) likelihood that a startup obtains a financing round each year, (b) amount raised through a financing round each year, and (c) likelihood that a startup experiences an IPO or an acquisition. The $Tech.SimilarStartup_{i,j}$ indicator takes a value of one if a startup i belongs to the treatment group and a value of zero if a startup i belongs to the control group. The variable $PostMisconduct_{j,t}$ takes the value of one for the five-year period since the misconduct allegation j is reported for the first time in the news; and a value of zero for the five-year period before the misconduct allegation being reported in the news. The coefficient of interest is β_2 measuring the average change in a treatment group's performance, post misconduct allegations and relative to the control group.

There may be an empirical concern that the exposure to a given misconduct allegation is unlikely to be random. Such an exposure may be correlated with factors, including characteristics of an observed startup and the associated misconduct allegation, as well as life cycle, technology, and geographical trends that could affect the outcomes in Equation (1). We introduce control variables and a set of fixed effects in our primary specification to address this concern. In particular, ω_i denotes the fixed effect for startup i that fully accounts for time-invariant differences between startups. We introduce the natural logarithm of startup age to control for its life cycle. The ϕ_j represents the fixed effect for misconduct allegation j. Moreover, we introduce $\theta_{k,t}$ to control for any sector-specific time-varying unobservable heterogeneities. $\tau_{s,t}$ is a state-by-year fixed effect controlling for any time-varying geographical trends, while $\epsilon_{i,j,k,s,t}$ is the idiosyncratic error term. Finally, our standard errors are clustered at the level of misconduct.

6 Results

In this section, we report the main effects of misconduct allegations on likelihood of raising a financing round, followed by amount raised and exit outcomes by the treatment group relative to the control group. For the sake of brevity, we refer to innocent startups developing similar technologies as the perpetrator as the treatment group, and innocent startups developing dissimilar technologies and located in a different state as the control group hereon, unless otherwise explicitly mentioned.

6.1 Effect on Raising a Financing Round

Panel A in Table 2 presents the regression results with the dummy for obtaining a financing round each year as the dependent variable. In Column (1), we provide the basic DID variables with the fixed effects for sector interacted with year. The results from the full model as specified in Equation (1) with all the fixed effects is provided in Column (4). Our primary variable of interest, namely $PostMisconduct_{j,t} * Tech.SimilarStartup_{i,j}$, is consistent in terms of economic and statistical significance across these models. In comparison to control group, our treatment group is likely to experience a 2.66 percentage points reduction in obtaining a financing round after the misconduct allegations become public knowledge. This translates into a reduction of 11 percent in obtaining a financing round for the treatment group, relative to the control group.

[Insert Table 2 here]

In Figure 1(a), it is evident that the estimated difference between treatment and control group is statistically non-significant before the misconduct allegation becomes public knowledge. The probability of obtaining a financing round for the treatment group reduces by 1.3 percentage points during the first year after misconduct allegation, relative to control group. This reduction becomes even more pronounced as time moves on. We find that the largest reduction in the probability of about 3.1 percentage points is experienced during the third year from the misconduct allegations. From thereon, treatment group experience lower probability of obtaining a financing round, about 2.7 percentage points on average, till the eighth year since the misconduct, relative to the control group. As theorized, the negative effect of the misconduct allegation is both immediate and persistent affecting the startups that develop similar technologies in the long run.

[Insert Figure 1 here]

We provide two sets of robustness checks in Column (5) and (6) to alleviate any concerns of sample selection. In Column (5), we re-estimate our Equation (1) with the sub-sample of startups that were not acquired at all. This is to alleviate any concern that our sample may constitute startups with different valuations. For instance, startups developing similar technologies and valued higher could decide not to obtain a financing round after the misconduct owing to the risk of a down round; thereby, driving the negative effect of misconduct estimated in our primary regression. We make use of the information on acquisition to address this concern. The intuition is that startups that have higher valuation are more likely to be acquired. By selecting a sub-sample of startups that were not acquired, we attempt to ensure that our sample constitutes of startups with similar valuations. The co-efficient of our variable of interest, $PostMisconduct_{j,t} * Tech.SimilarStartup_{i,j}$, indicates a reduction of 2.05 percentage points in probability of obtaining a financing round which is similar in both economic and statistical significance to the co-efficient from our primary regression provided in Column (4). In Column (6), we re-estimate our Equation (1) by changing the control group to those that are developing dissimilar technologies and located in the same state as the misconduct perpetrator. We adopted a very conservative criterion, especially the location, in selecting the original control group to ensure that it is not contaminated by any spillover effect of the misconduct allegations. We relax this criterion to check whether our primary results hold irrespective of the change in the control group. The co-efficient of our variable of interest is similar in both economic and statistical significance. Both these robustness checks provide re-assurance of the estimated effect from our primary regression. In sum, our evidence shows that a misconduct allegation results in an overwhelming negative effect for startups developing similar technologies, as the perpetrator, relative to those that develop dissimilar technologies and located in a different state.

6.2 Effect on Amount Raised

Panel B in Table 2 presents the regression results with the log of amount raised in a given round during a particular year as the dependent variable. The results from the full model as specified in Equation (1) with all the fixed effects is provided in Column (4). The estimated difference reveals that the treatment group raises lesser funds relative to the control group after the misconduct allegations becomes public knowledge. In essence, the news about the misconduct allegation reduced the amount raised by startups developing similar technologies by 31 percent relative to the control group.

Figure 1(b) plots the estimated difference in log of amount raised between the treatment and control group. We observe a similar pattern in reduction in amount raised for the treatment group as the probability of raising a financing round relative to the control group. To explain, we observe an immediate negative effect wherein the treatment group experience 17 percent fewer funds, relative to the control group, during the year in which the misconduct is first reported in the news. The most pronounced negative effect of 37 percent in amount raised for the treatment group was observed during the third year since the misconduct was reported. This is followed by a persistent negative effect where the treatment group raises 32 percent fewer funds, on average, between the fourth and tenth year since the misconduct allegation was reported.

As previously explained in sub-section 6.1, we re-estimate our primary regression with two sets of robustness checks provided in Column (5) and (6). Our results are similar in economic and statistical significance even after selecting the sub-sample of startups which were non-acquired and altering the control group to those that are in the same state as the misconduct perpetrator. In sum, startups developing similar technologies raise far fewer funds than those developing dissimilar technologies and located in a different state; in addition, the negative effect of the misconduct on amount raised continues to persist over a ten-year period.

6.3 Effect on Geographically Proximate Startups

We had theorized under hypotheses 2a and 2b that geographical proximity to the perpetrator could satisfy the relevance condition for investors to initiate genuine and strategic terminations as the misconduct allegations becomes public knowledge. To test this, we constructed a balanced sample wherein treatment group are those startups that are in the same state as the perpetrators. Our control group are those startups that are developing dissimilar technologies and located in different state as the misconduct perpetrator.

The regression results from the full model as specified in Equation (1) is provided in Column (4) of Table 3. Panel A and B present the results of probability of obtaining a financing round and log of amount raised, respectively, as the dependent variable.

[Insert Table 3 here]

[Insert Figure 2 here]

Our results show that startups that are geographically proximate do experience a reduction in probability of raising a round and log of amount raised, yet the level of reduction is not statistically significant relative to the control group. This becomes evident when we observe the estimated difference before and after a misconduct allegation plotted in Figure 2. Take Panel (B) in Figure 2 with log of amount raised as the dependent variable, startups that are geographically proximate to the misconduct perpetrator experience trivial reduction in amount raised in the initial years since the misconduct. We find that the reduction in the amount raised is statistically significant (at ten percent level) of about 5-6 percent during the second and third year since the misconduct. However, the negative effect dissipates and becomes statistically insignificant thereafter. Overall, we can conclude that there is no strong evidence to support our hypotheses 2a and 2b that misconduct allegations negatively impact innocent startups that are geographically proximate to the misconduct perpetrator.

6.4 Interrelated Effect of Technology and Origin based Generalization

The evidence suggests that sophisticated investors employ a nuanced categorization, specifically utilizing the technology category while disregarding consideration based on origin, to associate misconduct allegation with innocent startups. We have treated technology and origin factors as orthogonal in nature. But there is an intriguing avenue for exploration regarding whether investors consider these two factors in an interrelated manner to generalize culpability to innocent startups. To investigate this, we constructed a balanced dataset and created four distinct categories that account for the overlap between perpetrators and innocent startups, namely: (a) those developing similar technology and located in same state (ST-SS hereon), (b) those developing similar technology and located in different state (ST-DS hereon), (c) those developing dissimilar technology and located in same state (DT-SS hereon), and (d) those developing dissimilar technology and located in different state (DT-DS hereon). In our primary regression, which closely resembles Equation (1), we introduce a modification to the interaction term, incorporating the interrelated categorization as denoted by $Tech - StateSimilarStartup_{i,j}$. In this specification, innocent startups developing dissimilar technology and located in different state as the perpetrator serve as the control group. The regression results from the full model with probability of obtaining a financing round and log of amount raised is provided in Column (4) of Panel A and Panel B, respectively, in Table 4.

[Insert Table 4 here]

We find that innocent startups with ST-SS and ST-DS experience a reduction in likelihood of obtaining a financing round by 4.33 and 3.46 percentage points, respectively, relative to those with DT-DS, after a misconduct allegation is reported for the first time. Similarly, we find that innocent startups with ST-SS and ST-DS raise fewer funds by 47 and 38 percent, respectively, relative to the control group, after the misconduct allegation is reported for the first time. It is important to note that the difference in coefficients between innocent startups with ST-SS and ST-DS is not statistically significant. On the other hand, innocent startups with DT-SS do not experience any statistically significant effect in their likelihood of obtaining a financing round and amount raised after a misconduct allegation is reported for the first time. In Column (5), we re-estimate our specification with sub-sample of startups that were not acquired at all. The results are similar in nature, thereby providing confidence in our estimates from the full model. In sum, the evidence highlights that technology-specific similarity between innocent startups and perpetrators form the primary channel through which the negative effect of misconduct allegation is propagated in the entrepreneurial landscape. Investors do not attribute the misconduct allegations to a specific geographic location despite the negative perception of "Silicon Valley" culture emanating from numerous anecdotal discussions.

6.5 Heterogeneous Effect by Risk Manageability

We explore whether the negative effect observed for probability of obtaining a financing round and log of amount raised each year varies by expectations around the manageability of risks introduced by misconduct allegations. Remember that, under hypothesis 3, we postulated that misconduct allegations posing unmanageable risks to have substantial negative effect relative to those posing manageable risks. In addition, we categorized intellectual property infringements as manageable risks and the other three misconduct allegations – namely technological misconduct, financial fraud, and sexual harassment – as unmanageable risks. We introduce a tripe-interaction of $PostMisconduct_{j,t} * Tech.SimilarStartup_{i,j} * MisconductType_i$ in our primary Equation (1) with the treatment group being those innocent startups developing similar technologies as the perpetrator, and control group constituting innocent startups developing dissimilar technologies and located in a different state. Here, $MisconductType_i$ is a categorical variable representing the different types of misconduct allegations.[21]

The marginal effects of the different types of misconduct allegations are presented in Table 5 – where Panel (A) and (B) reports the results for probability of obtaining a financing round and log of amount raised each year as the dependent variable, respectively.

[Insert Table 5 here]

Focusing on Panel (A), we find that the largest negative effect on treatment group of 5.4 percentage points in probability of raising a financing round is associated with misleading claims of technological advancements, relative to the control group after the misconduct allegation becomes public knowledge. This is followed by sexual harassment and financial fraud which reduced the probability of raising a financing round by 4.1 and 2.0 percentage points, respectively, for our treatment group, relative to the control group. On the other hand, intellectual property infringements do not have a statistically significant effect on the treatment group, relative to the control group.

Considering the log of amount raised as the dependent variable, we find a similar pattern of economic and statistical significance across different types of misconduct allegations. Focusing on Panel (b) in Table 5, it is evident that the largest negative effect on the treatment group of 55 percent reduction in amount raised is associated with misleading claims of technological advancements, relative to the control group. Sexual harassment and financial fraud are associated with 44 percent and 23 percent reduction in amount raised for the treatment group, relative to the control group, after these allegations are reported in the news. In contrast, intellectual property infringements are not associated with statistically significant effects on the treatment group, relative to the control group. Overall, we can conclude that misconduct allegations posing unmanageable risks induce substantial and statistically significant negative effects on the financing opportunities of innocent startups developing similar technology as the perpetrators.

6.6 Heterogeneous Effect by Ex-Ante Uncertainty Level

We examine whether ex-ante uncertainty plays a significant role in investors decision-making towards innocent startups after the misconduct allegations were reported for the first time. We make use of the fact that early-stage startups deal with higher uncertainty relative to late-stage startups to investigate this question. We define innocent startups as early-stage if it had raised up to Series B before the misconduct allegations were reported; and late-stage startups are those that had raised be-

[21] Note that our decision to introduce a categorical variable representing different types of misconduct allegations, rather than a binary variable representing risk manageability, to leverage the entire dataset to reveal the varying degree of negative effect of different types of misconduct allegations. We make use of the marginal effects to qualitatively infer whether our hypothesis 3 holds or not.

yond Series B before the misconduct allegations were reported. We introduce a tripe-interaction of $PostMisconduct_{j,t} * Tech.SimilarStartup_{i,j} * Ex - antestage_{i,j}$ in our primary equation (1) and make use of margins command in STATA to retrieve the marginal effects of a misconduct by the ex-ante uncertainty level. Panel (A) and (B) in Table 6 present the results for probability of obtaining a financing round and log of amount raised each year as the dependent variable, respectively.

[Insert Table 6 here]

We find that early-stage innocent startups developing similar technology, as the perpetrator, face a decrease in likelihood of obtaining a financing round by 2.10 percentage points. Additionally, these startups experience a 24 percent reduction in amount of funds raised after a misconduct allegation is reported. In contrast, late-stage innocent startups developing similar technology, as the perpetrator, do not exhibit significant differences in their likelihood in obtaining a financing round and amount of funds raised after a misconduct allegation is reported. Our evidence indicates that misconduct allegations affect early-stage innocent startups that share technological similarities with the perpetrator in a more pronounced manner than late-stage innocent startups. In essence, misconduct allegation exacerbates the challenges of early-stage innocent startups developing similar technology, especially during the critical stages of development and potentially end up in the "valley of death" curve.

6.7 Unpacking the Potential Mechanism – Investors Behavior

6.7.1 VCs vs non-VCs

We explore the behavior of investors in their participation in a financing round and investment after a misconduct allegation becomes public knowledge. We explore which type of investors are more sensitive to these misconduct allegations – venture capitalists (VCs) or non- venture capitalists (non-VCs), such as individual investors. Conti et al. ,2019, argue that non-financial endowments of VCs may equip them better in reacting to a supply-side shock and invest more in their core sectors. On the other hand, non-VCs may have lower non-financial endowments, relative to VCs, thereby more likely to react negatively to a misconduct allegation. In addition, they are more likely to undertake strategic terminations under the guise of misconduct allegations (Grenadier et al. ,2014). Given this, we posit that non-VCs are less likely to participate in a financing round and/or invest less after a misconduct allegation relative to VCs. To test this, we construct dependent variables: (a) dummy variable which is 1 if a VC had participated in a financing round, and 0 otherwise; and (b) log of amount raised in a financing round in which a VC had participated. We construct similar dependent variables for participation and investment in a financing round during a given year for non-VCs.

[Insert Table 7 here]

In Table 7, Column (1) and (2) presents the results from our primary model for the probability of raising a financing round and log of amount raised with VC participation, respectively, whereas Column (5) and (6) presents the same with non-VC participation. Beginning with the probability of obtaining a financing round, we find that VCs and non-VCs are 1.04 and 1.62 percentage points, respectively, less likely to participate in a financing round of the treatment group relative to control group, once the allegation becomes public knowledge. While we do not conduct a statistical test, the qualitative difference indicates that non-VCs are more sensitive to misconduct allegations relative to VCs. Similar patterns are observed when we regress with log of amount raised with a VC and Non-VC participation as the dependent variable, as represented in Column (2) and (6) respectively. We find that the treatment group raises fewer funds – 14 percent and 20 percent – from VCs and Non-VCs, respectively, relative to the control group.

We go a step further and investigate whether prominent VCs decide to participate and invest less in a financing round after a misconduct. The trade-off is not apriori clear. It is true that prominent VCs should have relatively more non-financial endowments which should enable them to identify and nurture promising startups much more effectively. Therefore, misconduct allegations should have minimal effect on prominent-VCs decision to invest in innocent startups developing similar technologies as the perpetrators. On the other hand, misconduct allegations could heighten uncertainty over exit opportunities of these innocent startups; thereby inducing them not to participate in financing rounds. To test this, we construct the following dependent variables: (a) dummy variable which is 1 if a prominent VC had participated in a financing round, and 0 otherwise; and (b) log of amount raised in a financing round in which a prominent VC had participated. We define prominence by the top 500 investors based on amount invested across our entire sample of startups. The regression results are provided in Column (3) and (4) in Table 7.

It becomes evident that the prominent VCs participate and invest less in a financing round in startups developing similar technologies, relative to those developing dissimilar technologies and located in a different state, after a misconduct allegation. Prominent VCs are associated with negative effects of about 0.8 percentage points and 11 percent in participating and investing in a financing round, respectively. Our evidence suggests that misconduct allegations affect prominent VCs expectations about innocent startups developing similar technologies as the perpetrator and choose not to leverage their resources to nurture ventures that may still hold potential for a successful outcome.

6.7.2 Core vs Non-Core Sectors

We have established that investors react negatively when a misconduct allegation becomes public knowledge. It is still important to unravel this mechanism further to understand whether the investment decision varies between the core and non-core sectors of investors. Conti et al (2019) show that VCs alter their investment strategies by investing more in their core sector in reaction to a supply-side shock. Given this, we posit that investors could decide to participate and invest less in startup developing similar technologies, as the misconduct perpetrator, if the technological area is not part of their core sector. On the other hand, in the case of startups developing similar technologies being in their core sector, investors could avail tacit knowledge to determine a startup's potential outcome. In addition, investors may want to protect their reputation of being reliant and guide the startups developing similar technologies during such challenging periods – especially if it belongs to their core sector. Therefore, we can expect the negative reaction of investors to be moderated by whether the misconduct allegations occur in their core or non-core sectors.

To test this, we define core sectors based on the participation of an investor (VC / prominent VC / non-VC) during the ten-year period [-13,-4] before the establishment of a misconduct perpetrator.[22] A sector is assigned the core-sector status if it constituted more than or equal to 50 percent of investor's portfolio, based on participation in rounds, during the ten-year period.[23] Then, we constructed dependent variables wherein: (a) dummy variable that is 1 if a VC had participated in a financing round of a startup that belongs to the core sector, and 0 otherwise; (b) dummy variable that is 1 if a VC had participated in a financing round of a startup that belongs to the non-core sector, and 0 otherwise. The regression results are provided in Column (2) and (3) in Table 8 respectively. We replicate this process to construct dependent variables for prominent VCs and non-VCs as well.

[Insert Table 8 here]

As expected, we find that negative reaction by VCs varies by the nature of sectors wherein the likelihood of participating in a round of an innocent startup belonging to their core and non-core sectors

[22]For instance, Tesla was founded in 2003 therefore the ten-year period covers all investments that each investor participated between 1990-1999.

[23]We make use of the formula $C_{m,k,t} = \frac{N_{m,k,t}*100}{TN_{m,t}}$ where $N_{m,k,t}$ represents the number of financing rounds an investor (m) participated in a startup belonging to a sector (k) during the ten-year period (t); and $TN_{m,t}$ represents the total number of financing rounds an investor (m) participated in during the ten-year period (t). A sector is assigned to be an investor's core sector if $C_{m,k,t} \geq 50\%$; and non-core sector otherwise.

reduces by 0.33 and 1.13 percentage points, respectively. We find similar variation in likelihood of participation in round raised by the treatment group for prominent VCs and non-VCs by core and non-core sectors. Our results show that prominent VCs reduce their likelihood of participating in a round by 0.25 and 0.96 percentage points by their core and non-core sectors, respectively (see Column 4 and 5 in Table 8). Similarly, non-VCs reduce their likelihood of participating in a round by 0.21 and 0.74 percentage points by their core and non-core sectors, respectively (see Column 6 and 7 in Table 8).

[Insert Table 9 here]

Moving to amount invested by investors, we constructed another set of dependent variables wherein: (a) log of amount raised in a round in which the VC participated in and belongs to their core sector; and (b) log of amount raised in a round in which the VC participated in and belongs to their non-core sector. The regression results are provided in Column (2) and (3) in Table 9 respectively. We construct similar dependent variables for prominent VCs and non-VCs. We find that VCs reduce their investments in the treatment group belonging to their non-core sectors much more (-15 percent) relative to those in core sectors (-5 percent) after a misconduct allegation is reported in the news. We find a similar pattern for prominent investors and non-VCs. For prominent VCs, they reduce their investments in the treatment group belonging to their non-core sectors much more (-14 percent) relative to those in core sectors (-4 percent) after a misconduct allegation is reported in the news (see Column 4 and 5 in Table 9). For non-VCs, the reduction in investments in the treatment group belonging to their non-core sectors is about 10 percent relative to 3 percent in their core sectors. Overall, our evidence suggests that investors react much more negatively to misconduct allegations in sectors that belong to their non-core sectors.

We undertake a robustness check by changing the definition of core and non-core sectors. The alternative definition is based on the amount raised in rounds in which a particular investor participated in.[24] The regression results for likelihood of participating in a round and log of amount raised based on this alternative definition is provided in Appendix Table A6 and A7 respectively. The results are similar in nature of direction and magnitude, in addition to similar patterns of difference in investment decisions by investors in the treatment group belonging to their core and non-core sectors.

[24]We undertake a robustness check by changing the definition of core and non-core sector. The alternative definition is based on the amount raised in rounds in which a particular investor participated in. We make use of the formula $C_{m,k,t} = \frac{A_{m,k,t}*100}{TA_{m,t}}$ where $A_{m,k,t}$ represents the amount raised in a financing rounds an investor (m) participated in a startup belonging to a sector (k) during the ten-year period (t); and $TA_{m,t}$ represents the total amount raised in financing rounds an investor (m) participated in during the ten-year period (t). A sector is assigned to be an investor's core sector if $C_{m,k,t} \geq 50\%$; and non-core sector otherwise.

6.8 Effect on Exit Opportunities

We explore whether a misconduct event affects the exit opportunities – initial public offering (IPO) and acquisition, of innocent startups developing similar technologies relative to those developing dissimilar technologies and located in a different state. To do this, we construct three dependent variables namely: (a) dummy variable of 1 if a startup experienced an acquisition / IPO, and 0 otherwise; (b) dummy variable of 1 if a startup experienced an IPO, and 0 otherwise; and (c) dummy variable of 1 if a startup experienced an acquisition, and 0 otherwise.

[Insert Table 10 here]

Columns (2), (4), and (6) in Table 10 provide the results for the full model with all exit opportunities (IPO/acquisition), IPO only, and acquisition only, respectively. Across three dependent variables, we find that the primary variable of interest - $PostMisconduct_{j,t} * Tech.SimilarStartup_{i,j}$ is not statistically significant. This indicates that the treatment group is as likely to experience a successful exit as our control group after a misconduct allegation is first reported in the news. This is in contradiction of our hypothesis as expected that the increase in financing risk for these innocent startups, owing to misconduct allegations, would translate into a reduction in the likelihood of exit opportunities. A potential rationale could be the duration between misconduct allegations and time at which these innocent startups approach the exit market. It is possible that salience of misconduct allegation reduces drastically over time, and this could play a significant role in determining the exit opportunities of these startups.

7 Discussion & Conclusions

Technological revolutions offer immense promise of disrupting the market creating conditions for hot markets. Ewens et al. ,2018, document that such revolutions have promoted investors to adopt an experimentation approach to investing in new ventures. While this has resulted in funds being available for a larger number of startups, it has also induced investors to move away from playing an active role in governance to a much limited one. These conditions have provided fertile grounds for innovative, yet riskier, ventures to obtain much-needed funding to operationalize their ideas. But more importantly, it has also attracted opportunistic individuals to establish startups claiming to use these new technologies – despite lacking in pre-requisite technical and governance competence – to capture the inflow of new investments. The combination of these factors has escalated the potential for illegitimate practices to flourish and its subsequent public revelation in the form of misconduct allegations. Our descriptive evidence supports this as we observe that most of the misconduct allegations involve new and innovative technologies.

In this paper, we examine whether such misconduct allegations affect the financing opportunities of innocent startups. Extant literature provides empirical evidence on the effect of common shocks, such as dotcom and financial crisis, in creating financial constraints for startups as investors alter their investment strategies and minimize experimenting with innovative, yet riskier, startups (Conti et al. ,2019; Townsend ,2015). Further, Grenadier et al. ,2014, theorize that higher likelihood of a common shock can motivate investors to delay terminations of their venture to protect their reputation. The authors argue their investors could undertake strategic terminations under the guise of a common shock. Our work contributes to this inquiry by examining investors' reactions to idiosyncratic shocks such as misconduct allegations.

Using a stacked difference-in-difference estimation, our empirical evidence supports our premise that misconduct allegations result in negative effects on the financing opportunities of innocent startups. Unlike Grenadier et al. ,2014, our work establishes that not all investors can undertake strategic terminations under the guise of misconduct allegations. It is only those innocent startups that share certain relevant characteristics with the perpetrators who get affected by these misconduct allegations being reported in the news. Our estimation results reveal that investors are less likely to participate in a financing round and invest less in innocent startups that develop technology similar to the perpetrators – transcending geographical boundaries within the US. However, this negative effect of misconduct allegations does not spill over to innocent startups that are geographically proximate to the perpetrators. This finding has implications for how entrepreneurs organize their financial resource mobilization (Hallen & Eisenhardt ,2012; Huang & Pearce ,2015; Murray & Fisher ,2023). Our evidence suggests that entrepreneurs may have to consider the tradeoff between enhanced financing opportunities by association with new technologies and exposure to financial constraints owing to the higher likelihood of revelations of misconduct allegations, which could affect the long-term viability of their ventures.

This study also lays emphasis on the value-added role of investors (Hsu ,2007; Nahata ,2008) especially their reputation to manage risks, guide ventures during challenging periods, and obtain successful exit outcomes. We theorize and empirically show that there exist incentives for investors to protect this reputation thereby moderating their reaction to different types of misconduct allegations. We argue that misconduct allegations posing unmanageable risks allure pronounced negative reactions from investors, whereas those posing manageable risks would only result in minimal reaction from investors. Consequently, we categorized technological misconduct, sexual harassment, and financial fraud under unmanageable risk, and intellectual property infringements under manageable risk. We find the strongest negative effects are associated with technological misconduct and sexual harassment, followed by financial misconduct, whereas the impact of intellectual property infringements is statistically insignificant. Further, back-of-the-envelope estimation indicates that innocent startups developing similar technology, as the perpetrators, potentially lose about US $ 0.42 million, on average, in investment over the five-year period after the misconduct allegation becomes public knowledge. The potential loss in investment for technologically similar startups varies about US $ 0.90 million, US $ 0.61 million, and US $ 0.37 million as technological misconduct, sexual harassment, and financial fraud, respectively, becomes public knowledge.

Our findings add to the evidence on the role of uncertainty in propagating negative effects of failure/misconducts (Krieger ,2021; Naumovska & Zajac ,2022). We theorize that investors investing in early-stage startups face a higher degree of uncertainty thereby inducing them to alter their investment strategies as the misconduct allegations were reported, relative to those investing in late-stage startups. Our estimation results support this as we observe that early-stage technologically similar innocent startups are 2 percentage points less likely to obtain a financing round and raise 24 percent fewer funds after the misconduct allegation becomes public knowledge, relative to those that are technologically dissimilar and located in different state. In contrast, the late-stage technologically similar startups do not experience statistically significant effect on their likelihood of obtaining a financing round and amount raised from investors. Moreover, this insight addresses the dearth in our understanding of conditions that contribute to early-stage startups falling into the "valley of death" curve.

The heterogenous effects of misconduct allegations by the expectation over risk manageability and different stages of innocent startups point towards the role of information asymmetry in this context. From our results, we can infer that higher (lower) information asymmetry propagates (mitigates) the negative effects of misconduct allegations. Extant literature provides us with insights into different mechanisms, such as signaling and information transfer, through which entrepreneurs can reduce the problem of information asymmetry between themselves and prospective investors (Colombo ,2021; Shane & Cable ,2002). In the case of financial misconduct, Paruchuri & Misangyi ,2015, document that investors perception about the governance structure moderate the negative effects on innocent firms. In a similar vein, entrepreneurs can take into consideration instituting a strong governance mechanism to signal to the external stakeholders. In addition, it offers opportunities for entrepreneurs to effectively disclose information about the risk exposure to different obstacles in a periodic manner. This can influence external stakeholders' perceptions of manageability of risk introduced by a misconduct allegation, thereby curtailing the chances of strategic terminations by investors. Finally, our evidence reveals that investors' tacit knowledge about their investment sectors influences their change in investment strategies after a misconduct allegation is revealed. We find that investors who experiment by investing in non-core sectors, outside their traditional investment spaces, exhibit more sensitive to negative information, such as misconduct allegations, relative to those who invest in their core sectors. This evidence holds true for various types of investors – VCs, prominent VCs, and non-VCs. This emphasizes the importance of choosing investors by entrepreneurs for their venture – especially those investors with the reputation of adding value by being reliable and competent (Aggarwal, Kryscynski, & Singh ,2015; Hallen & Pahnke ,2016; Hsu ,2004; Khanna & Mathews ,2022).

While we have attempted to comprehensively understand the effects of misconduct allegations on innocent startups, there are still intriguing avenues that can be explored in future studies. First, and foremost, there could be advocates and detractors of the role of misconduct allegations in enhancing efficiency in the market. Grenadier et al. ,2014, argue that shocks, such as misconduct allegations, can induce investors to terminate under-performing ventures, which they may have continued to invest in to protect their reputation. Therefore, it serves as an important role in clearing the market of inefficient ventures. However, it can be argued that such strategic terminations can inadvertently result in abandonment of healthy and innovative ventures – which may have succeeded conditional upon subsequent investments. It is then important to understand the proportion of underperforming and healthy ventures that face financial constraints and potential closure to determine whether misconduct allegations enhance or engender the welfare of entrepreneurs and investors.

Second, we have examined only two of the relevance characteristics through which culpability of misconduct allegations can be transmitted to innocent startups. An important characteristic is the founders' characteristics which has been identified to play a crucial role in investors' subjective judgements determining their investment decisions (Colombo ,2021; P. A. Gompers & Lerner ,1995). It can be argued that similarity in founders' characteristics between innocent startups and perpetrators can transmit the negative effects. However, there are two other mechanisms such as founders' own reputation and similarity between founders and investors that can mitigate/propagate the negative effects of misconduct allegations (Hegde & Tumlinson ,2014; Ko & McKelvie ,2018; Tzabbar & Margolis ,2017). For instance, there were anecdotal discussions about the negative effect on female founders and financing opportunities of their ventures as the Theranos misconduct unraveled in public domain. Additionally, misconduct allegations could stimulate prevailing biases of investors and transmit culpability based on founders' race, gender, and origin (Kanze, Huang, Conley, & Higgins ,2018; Mueller & Reus ,2022). This could result in not only impacting the financing opportunities but also founding opportunities for these potential entrepreneurs.

Finally, our evidence suggests that negative effect of misconduct allegations transcends state boundaries within US. It would be interesting to explore whether misconduct allegations affect the flow of investments from the US to other emerging clusters such as Israel, India, and others. This has implications for both domestic and international policymakers to take cognizance of the role of idiosyncratic shock, such as misconduct allegations, in influencing the financing and founding opportunities in the global entrepreneurial landscape.

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References

Aggarwal, R., Kryscynski, D., & Singh, H. (2015). Evaluating venture technical competence in venture capitalist investment decisions. *Management Science*, *61*(11), 2685–2706.

Baker, A. C., Larcker, D. F., & Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, *144*(2), 370–395.

Baker, B., Derfler-Rozin, R., Pitesa, M., & Johnson, M. (2019). Stock market responses to unethical behavior in organizations: An organizational context model. *Organization Science*, *30*(2), 319–336.

Bergemann, D., Hege, U., & Peng, L. (2009). Venture capital and sequential investments.

Bernstein, S., Giroud, X., & Townsend, R. R. (2016). The impact of venture capital monitoring. *The Journal of Finance*, *71*(4), 1591–1622.

Bleiberg, J. (2021). Stackedev: Stata module to implement stacked event study estimator.

Bloom, N., Bond, S., & Van Reenen, J. (2007). Uncertainty and investment dynamics. *The review of economic studies*, *74*(2), 391–415.

Bottazzi, L., Da Rin, M., & Hellmann, T. (2008). Who are the active investors?: Evidence from venture capital. *Journal of financial economics*, *89*(3), 488–512.

Bottazzi, L., Da Rin, M., & Hellmann, T. (2016). The importance of trust for investment: Evidence from venture capital. *The Review of Financial Studies*, *29*(9), 2283–2318.

Bruyaka, O., Philippe, D., & Castañer, X. (2018). Run away or stick together? the impact of organization-specific adverse events on alliance partner defection. *Academy of Management Review*, *43*(3), 445–469.

Burns, N., & Kedia, S. (2006). The impact of performance-based compensation on misreporting. *Journal of financial economics*, *79*(1), 35–67.

Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, *134*(3), 1405–1454.

Chahine, S., Filatotchev, I., Bruton, G. D., & Wright, M. (2021). "success by association": the impact of venture capital firm reputation trend on initial public offering valuations. *Journal of Management*, *47*(2), 368–398.

Chakraborty, I., & Ewens, M. (2018). Managing performance signals through delay: Evidence from venture capital. *Management Science*, *64*(6), 2875–2900.

Chen, X.-P., Yao, X., & Kotha, S. (2009). Entrepreneur passion and preparedness in business plan presentations: a persuasion analysis of venture capitalists' funding decisions. *Academy of Management journal*, *52*(1), 199–214.

Ciuchta, M. P., Letwin, C., Stevenson, R., McMahon, S., & Huvaj, M. N. (2018). Betting on the coachable entrepreneur: Signaling and social exchange in entrepreneurial pitches. *Entrepreneurship Theory and Practice*, *42*(6), 860–885.

Colombo, O. (2021). The use of signals in new-venture financing: A review and research agenda. *Journal of Management*, *47*(1), 237–259.

Conti, A., Dass, N., Di Lorenzo, F., & Graham, S. J. (2019). Venture capital investment strategies under financing constraints: Evidence from the 2008 financial crisis. *Research Policy*, *48*(3), 799–812.

Conti, A., & Roche, M. P. (2021). Lowering the bar? external conditions, opportunity costs, and high-tech start-up outcomes. *Organization Science*, *32*(4), 965–986.

Conti, A., Thursby, M., & Rothaermel, F. T. (2013). Show me the right stuff: Signals for high-tech startups. *Journal of Economics & Management Strategy*, *22*(2), 341–364.

Cumming, D., Dannhauser, R., & Johan, S. (2015). Financial market misconduct and agency conflicts: A synthesis and future directions. *Journal of Corporate Finance*, *34*, 150–168.

Dimmock, S. G., & Gerken, W. C. (2012). Predicting fraud by investment managers. *Journal of Financial Economics*, *105*(1), 153–173.

Dyck, A., Morse, A., & Zingales, L. (2010). Who blows the whistle on corporate fraud? *The journal of finance*, *65*(6), 2213–2253.

Efendi, J., Srivastava, A., & Swanson, E. P. (2007). Why do corporate managers misstate financial statements? the role of option compensation and other factors. *Journal of financial economics*, *85*(3), 667–708.

Ewens, M., & Farre-Mensa, J. (2020). The deregulation of the private equity markets and the decline in ipos. *The Review of Financial Studies*, *33*(12), 5463–5509.

Ewens, M., Nanda, R., & Rhodes-Kropf, M. (2018). Cost of experimentation and the evolution of venture capital. *Journal of Financial Economics*, *128*(3), 422–442.

Fich, E. M., & Shivdasani, A. (2007). Financial fraud, director reputation, and shareholder wealth. *Journal of financial Economics*, *86*(2), 306–336.

Giannetti, M., & Wang, T. Y. (2016). Corporate scandals and household stock market participation. *The Journal of Finance*, *71*(6), 2591–2636.

Gompers, P., Kovner, A., Lerner, J., & Scharfstein, D. (2008). Venture capital investment cycles: The impact of public markets. *Journal of financial economics*, *87*(1), 1–23.

Gompers, P. A. (2022). Optimal investment, monitoring, and the staging of venture capital. In *Venture capital* (pp. 285–313). Routledge.

Gompers, P. A., & Lerner, J. (1995). The use of covenants: An empirical analysis of venture partnership agreements. *Available at SSRN 6086*.

Grenadier, S. R., Malenko, A., & Strebulaev, I. A. (2014). Investment busts, reputation, and the temptation to blend in with the crowd. *Journal of Financial Economics*, *111*(1), 137–157.

Gurun, U. G., Stoffman, N., & Yonker, S. E. (2018). Trust busting: The effect of fraud on investor behavior. *The Review of Financial Studies*, *31*(4), 1341–1376.

Hallen, B. L., & Eisenhardt, K. M. (2012). Catalyzing strategies and efficient tie formation: How entrepreneurial firms obtain investment ties. *Academy of Management Journal*, *55*(1), 35–70.

Hallen, B. L., & Pahnke, E. C. (2016). When do entrepreneurs accurately evaluate venture capital firms' track records? a bounded rationality perspective. *Academy of Management Journal*, *59*(5), 1535–1560.

Hegde, D., & Tumlinson, J. (2014). Does social proximity enhance business partnerships? theory and evidence from ethnicity's role in us venture capital. *Management Science*, *60*(9), 2355–2380.

Hellmann, T., & Puri, M. (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. *The journal of finance*, *57*(1), 169–197.

Higgins, M. C., & Gulati, R. (2006). Stacking the deck: The effects of top management backgrounds on investor decisions. *Strategic Management Journal*, *27*(1), 1–25.

Howell, S. T. (2017). Financing innovation: Evidence from r&d grants. *American economic review*, *107*(4), 1136–1164.

Howell, S. T. (2020). Reducing information frictions in venture capital: The role of new venture competitions. *Journal of Financial Economics*, *136*(3), 676–694.

Howell, S. T., Lerner, J., Nanda, R., & Townsend, R. R. (2020). *How resilient is venture-backed innovation? evidence from four decades of us patenting* (Tech. Rep.). National Bureau of Economic Research.

Hsu, D. H. (2004). What do entrepreneurs pay for venture capital affiliation? *The journal of finance*, *59*(4), 1805–1844.

Hsu, D. H. (2007). Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research policy*, *36*(5), 722–741.

Hsu, D. H., & Ziedonis, R. H. (2013). Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal*, *34*(7), 761–781.

Huang, L., & Pearce, J. L. (2015). Managing the unknowable: The effectiveness of early-stage investor gut feel in entrepreneurial investment decisions. *Administrative science quarterly*, *60*(4), 634–670.

Jelic, R., Zhou, D., & Ahmad, W. (2021). Do stressed pe firms misbehave? *Journal of Corporate Finance*, *66*, 101798.

Jensen, M. (2006). Should we stay or should we go? accountability, status anxiety, and client defections. *Administrative Science Quarterly*, *51*(1), 97–128.

Jonsson, S., Greve, H. R., & Fujiwara-Greve, T. (2009). Undeserved loss: The spread of legitimacy loss to innocent organizations in response to reported corporate deviance. *Administrative Science Quarterly*, *54*(2), 195–228.

Julio, B., & Yook, Y. (2012). Political uncertainty and corporate investment cycles. *The Journal of Finance*, *67*(1), 45–83.

Kanze, D., Huang, L., Conley, M. A., & Higgins, E. T. (2018). We ask men to win and women not to lose: Closing the gender gap in startup funding. *Academy of Management Journal*, *61*(2), 586–614.

Karpoff, J. M., Lee, D. S., & Martin, G. S. (2008). The consequences to managers for cooking the books. *Journal of Financial Economics*, *88*(88), 193–215.

Kerr, W. R., Nanda, R., & Rhodes-Kropf, M. (2014). Entrepreneurship as experimentation. *Journal of Economic Perspectives*, *28*(3), 25–48.

Khanna, N., & Mathews, R. D. (2022). Skill versus reliability in venture capital. *Journal of Financial Economics*, *145*(2), 41–63.

Kirsch, D., Goldfarb, B., & Gera, A. (2009). Form or substance: the role of business plans in venture capital decision making. *Strategic Management Journal*, *30*(5), 487–515.

Ko, E.-J., & McKelvie, A. (2018). Signaling for more money: The roles of founders' human capital and investor prominence in resource acquisition across different stages of firm development. *Journal of Business Venturing*, *33*(4), 438–454.

Krieger, J. L. (2021). Trials and terminations: Learning from competitors' r&d failures. *Management Science*, *67*(9), 5525–5548.

Lerner, J. (2000). Assessing the contribution of venture capital. *the RAND Journal of Economics*, *31*(4), 674–692.

Lerner, J., & Kortum, S. (2000). Assessing the impact of venture capital on innovation. *Rand Journal of Economics*, *31*, 674–692.

Lerner, J., & Nanda, R. (2020). Venture capital's role in financing innovation: What we know and how much we still need to learn. *Journal of Economic Perspectives*, *34*(3), 237–261.

Manso, G. (2016). Experimentation and the returns to entrepreneurship. *The Review of Financial Studies*, *29*(9), 2319–2340.

McMullen, J. S., & Shepherd, D. A. (2006). Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur. *Academy of Management review*, *31*(1), 132–152.

Metrick, A., & Yasuda, A. (2010). The economics of private equity funds. *The Review of Financial Studies*, *23*(6), 2303–2341.

Mueller, M. J., & Reus, T. (2022). Exemplary outsiders? immigrant ceos and financial misrepresentation. In *Academy of management proceedings* (Vol. 2022, p. 16750).

Murray, A., & Fisher, G. (2023). When more is less: Explaining the curse of too much capital for early-stage ventures. *Organization Science*, *34*(1), 246–282.

Nagy, B. G., Pollack, J. M., Rutherford, M. W., & Lohrke, F. T. (2012). The influence of entrepreneurs' credentials and impression management behaviors on perceptions of new venture legitimacy. *Entrepreneurship Theory and Practice*, *36*(5), 941–965.

Nahata, R. (2008). Venture capital reputation and investment performance. *Journal of financial economics*, *90*(2), 127–151.

Nanda, R., & Rhodes-Kropf, M. (2013). Investment cycles and startup innovation. *Journal of financial economics*, *110*(2), 403–418.

Nanda, R., & Rhodes-Kropf, M. (2017). Financing risk and innovation. *Management science*, *63*(4), 901–918.

Naumovska, I., & Lavie, D. (2021). When an industry peer is accused of financial misconduct: Stigma versus competition effects on non-accused firms. *Administrative Science Quarterly*, *66*(4), 1130–1172.

Naumovska, I., & Zajac, E. J. (2022). How inductive and deductive generalization shape the guilt-by-association phenomenon among firms: Theory and evidence. *Organization Science*, *33*(1), 373–392.

Parsons, C. A., Sulaeman, J., & Titman, S. (2018). The geography of financial misconduct. *The Journal of Finance*, *73*(5), 2087–2137.

Paruchuri, S., & Misangyi, V. F. (2015). Investor perceptions of financial misconduct: The heterogeneous contamination of bystander firms. *Academy of Management Journal*, *58*(1), 169–194.

Plagmann, C., & Lutz, E. (2019). Beggars or choosers? lead venture capitalists and the impact of reputation on syndicate partner selection in international settings. *Journal of Banking & Finance*, *100*, 359–378.

Que, J., & Zhang, X. (2021). Money chasing hot industries? investor attention and valuation of venture capital backed firms. *Journal of Corporate Finance*, *68*, 101949.

Shane, S., & Cable, D. (2002). Network ties, reputation, and the financing of new ventures. *Management science*, *48*(3), 364–381.

Sørensen, M. (2007). How smart is smart money? a two-sided matching model of venture capital. *The Journal of Finance*, *62*(6), 2725–2762.

Stuart, T., & Sorenson, O. (2003). The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research policy*, *32*(2), 229–253.

Te, Y.-F., Wieland, M., Frey, M., Pyatigorskaya, A., Schiffer, P., & Grabner, H. (2023). Making it into a successful series a funding: An analysis of crunchbase and linkedin data. *The Journal of Finance and Data Science*, 100099.

Townsend, R. R. (2015). Propagation of financial shocks: The case of venture capital. *Management Science*, *61*(11), 2782–2802.

Tzabbar, D., & Margolis, J. (2017). Beyond the startup stage: The founding team's human capital, new venture's stage of life, founder–ceo duality, and breakthrough innovation. *Organization science*, *28*(5), 857–872.

Yin, C., Cheng, X., Yang, Y., & Palmon, D. (2021). Do corporate frauds distort suppliers' investment decisions? *Journal of Business Ethics*, *172*, 115–132.

Yue, L. Q., Rao, H., & Ingram, P. (2013). Information spillovers from protests against corporations: A tale of walmart and target. *Administrative Science Quarterly*, *58*(4), 669–701.

Zuckerman, E. W. (2000). Focusing the corporate product: Securities analysts and de-diversification. *Administrative science quarterly*, *45*(3), 591–619.

Zuckerman, E. W. (2012). Construction, concentration, and (dis) continuities in social valuations. *Annual Review of Sociology*, *38*, 223–245.

9 Tables

Table 1: Descriptive statistics of the treatment and control sample

Selected Independent Variables	Treatment Before	Treatment After	Difference between (2) and (1)	Control Before	Control After	Difference between (5) and (4)
	(1)	(2)	(3)	(4)	(5)	(6)
Obtained Financing Round	0.278	0.197	-0.081	0.138	0.105	-0.033
	[0.004]	[0.003]	[0.004]	[0.003]	[0.003]	[0.004]
Total Amt. Raised (in million US $)	5.394	8.440	3.046	1.458	2.795	1.337
	[0.282]	[0.555]	[0.620]	[0.088]	[0.260]	[0.274]
Total Amt. Raised from VC (in million US $)	3.397	4.277	0.879	0.754	1.328	0.575
	[0.234]	[0.271]	[0.358]	[0.060]	[0.149]	[0.160]
Exit	0.065	0.107	0.042	0.042	0.073	0.031
	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.003]
Acquisition	0.052	0.091	0.039	0.035	0.067	0.032
	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.003]
IPO	0.013	0.018	0.005	0.007	0.006	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Biotechnology	0.018		-	0.014		-
	[0.001]		-	[0.001]		-
Healthcare	0.190		-	0.024		-
	[0.003]		-	[0.003]		-
Software	0.469		-	0.564		-
	[0.004]		-	[0.004]		-
Developing New Technologies	0.790		-	0.639		-
	[0.003]		-	[0.004]		-
California	0.308		-	0.128		-
	[0.004]		-	[0.003]		-
Massachusetts	0.058		-	0.053		-
	[0.002]		-	[0.002]		-
New York	0.100		-	0.122		-
	[0.002]		-	[0.003]		-
N. Startups	15,406		-	15,406		-

Notes: This table reports the descriptive statistics of the treatment and control sample. We define treatment as innocent startups developing similar technologies as the perpetrator. We define control as innocent startups developing dissimilar technologies and located in a different state than the perpetrator. The summary statistics provide the unadjusted difference between the treatment and control startups over the period starting five years before a given misconduct event was reported for the first time in the news. The standard errors are reported in parentheses.

Table 2: Effect of misconduct allegations on startups that are technologically similar to the perpetrators

	Panel A: Likelihood of raising a financing round					
	(1)	(2)	(3)	(4)	(5)	(6)
Post misconduct	-0.0058	0.0103*	0.0085**	0.0100**	0.0084**	0.0130***
	(0.0074)	(0.0054)	(0.0040)	(0.0043)	(0.0036)	(0.0040)
Tech. similar startups	**-0.0333*****	**-0.0310*****	**-0.0264*****	**-0.0266*****	**-0.0205*****	**-0.0370*****
X Post misconduct	**(0.0101)**	**(0.0086)**	**(0.0074)**	**(0.0074)**	**(0.0055)**	**(0.0062)**
Ln. Startup Age		-0.0382***	0.0071	0.0079*	0.0019	-0.0002
		(0.0036)	(0.0045)	(0.0046)	(0.0043)	(0.0070)
Constant	0.0441***	0.1055***	0.0535***	0.0516***	0.0556***	0.0801***
	(0.0051)	(0.0047)	(0.0080)	(0.0085)	(0.0075)	(0.0118)
R2	0.0360	0.0517	0.3043	0.3044	0.3103	0.3066
Observations	288,378	288,351	288,317	288,317	239,126	162,035
	Panel B: Log of Amount Raised					
	(1)	(2)	(3)	(4)	(5)	(6)
Post misconduct	-0.0620	0.1458*	0.1131**	0.1314**	0.1082**	0.1885***
	(0.1080)	(0.0826)	(0.0562)	(0.0612)	(0.0504)	(0.0564)
Tech. similar startups	**-0.4803*****	**-0.4427*****	**-0.3703*****	**-0.3721*****	**-0.2668*****	**-0.5411*****
X Post misconduct	**(0.1517)**	**(0.1271)**	**(0.1066)**	**(0.1067)**	**(0.0755)**	**(0.0931)**
Ln. Startup Age		-0.4980***	0.2507***	0.2645***	0.1640***	0.1847**
		(0.0518)	(0.0597)	(0.0618)	(0.0595)	(0.0866)
Constant	0.6270***	1.4392***	0.5432***	0.5091***	0.5766***	0.8818***
	(0.0748)	(0.0715)	(0.1071)	(0.1133)	(0.1033)	(0.1491)
R2	0.0349	0.0501	0.3147	0.3148	0.3244	0.3168
Observations	288,378	288,351	288,317	288,317	239,126	162,035
Misconduct FE	N	N	N	Y	Y	Y
Startup FE	N	N	Y	Y	Y	Y
State X Year FE	N	Y	Y	Y	Y	Y
Sector X Year FE	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered at misconduct level					

Notes: This table reports the difference-in-difference model estimating the effect of misconduct events on the likelihood of raising a round (Panel A) and natural logarithm of the amount raised in a year t (Panel B) for a startup developing similar technologies as the perpetrator relative to those developing dissimilar technologies and located in a different state. We observe each startup over the period starting five years before a given misconduct event was reported for the first time in the news and ending five years after. Post-misconduct is an indicator that equals 1 in the period following the first occurrence of a misconduct allegation in the news and zero otherwise. Tech. similar startup is an indicator that equals 1 for startups developing similar technologies and 0 for startups developing dissimilar technologies and located in a different state than the perpetrator. We introduce the natural log of startup's age plus 1 to control for the startup life cycle from column (2) onwards. We progressively introduce our fixed effects starting with sector-with-year in Column (1), followed by state-with-year, startup, and misconduct level in Column (2), (3), and (4) respectively. In Column (5), we regress for the sub-sample of startups that have not been acquired. In Column (6), we introduce an alternative control defined as startups developing dissimilar technologies and located in the same state as the perpetrator. We cluster the standard errors at the misconduct level in all regressions and are reported in parentheses. Significance levels are noted as follows: * - $p < 0.10$; ** - $p < 0.05$; and *** - $p < 0.001$.

Table 3: Effect of misconduct allegations on startups that are geographically proximate to the perpetrators

	Panel A: Likelihood of raising a financing round				
	(1)	(2)	(3)	(4)	(5)
Post misconduct	-0.0204***	0.0006	-0.0072***	-0.0060**	-0.0045*
	[0.0042]	[0.0039]	[0.0023]	[0.0026]	[0.0025]
Geo. Proximate startups	**-0.0191*****	**-0.0145*****	**-0.0021**	**-0.0021**	**-0.0014**
X Post misconduct	**[0.0038]**	**[0.0035]**	**[0.0018]**	**[0.0018]**	**[0.0017]**
Ln. Startup Age		-0.0378***	-0.0064**	-0.0059**	-0.0092***
		[0.0024]	[0.0027]	[0.0027]	[0.0027]
Constant	0.0572***	0.1135***	0.0714***	0.0699***	0.0691***
	[0.0033]	[0.0037]	[0.0044]	[0.0045]	[0.0047]
R2	0.021	0.032	0.293	0.293	0.299
Observations	680,959	680,945	680,920	680,920	587,335
	Panel B: Log of Amount Raised				
	(1)	(2)	(3)	(4)	(5)
Post misconduct	-0.2471***	0.0113	-0.0970***	-0.0779**	-0.0540
	[0.0542]	[0.0558]	[0.0309]	[0.0358]	[0.0331]
Geo. Proximate startups	**-0.2747*****	**-0.2150*****	**-0.0283**	**-0.0276**	**-0.0178**
X Post misconduct	**[0.0584]**	**[0.0550]**	**[0.0282]**	**[0.0282]**	**[0.0246]**
Ln. Startup Age		-0.4738***	0.0665**	0.0746**	0.0136
		[0.0305]	[0.0333]	[0.0334]	[0.0350]
Constant	0.7850***	1.5256***	0.7786***	0.7536***	0.7586***
	[0.0414]	[0.0468]	[0.0550]	[0.0556]	[0.0604]
R2	0.020	0.029	0.305	0.306	0.315
Observations	680,959	680,945	680,920	680,920	587,335
Misconduct FE	N	N	N	Y	Y
Startup FE	N	N	Y	Y	Y
State X Year FE	N	Y	Y	Y	Y
Sector X Year FE	Y	Y	Y	Y	Y
Standard Errors	Clustered at the misconduct level				

Notes: This table reports the difference-in-difference model estimating the effect of misconduct events on the likelihood of raising a round (Panel A) and natural logarithm of the amount raised in a year t (Panel B) for a startup located in the same state as the perpetrator relative to those developing dissimilar technologies and located in a different state. We observe each startup over the period starting five years before a given misconduct event was reported for the first time in the news and ending five years after. Post-misconduct is an indicator that equals 1 in the period following the first occurrence of a misconduct allegation in the news and zero otherwise. Geo. Proximate startup is an indicator that equals 1 for startups located in the same state and 0 for startups developing dissimilar technologies and located in a different state than the perpetrator. We introduce the natural log of startup's age plus 1 to control for the startup life cycle from column (2) onwards. We progressively introduce our fixed effects starting with sector-with-year in Column (1), followed by state-with-year, startup, and misconduct level in Column (2), (3), and (4) respectively. In Column (5), we regress for the sub-sample of startups that have not been acquired. We cluster the standard errors at the misconduct level in all regressions and are reported in parentheses. Significance levels are noted as follows: * - $p < 0.10$; ** - $p < 0.05$; and *** - $p < 0.001$.

Table 4: Interrelated effect of misconduct allegations on innocent startups

	Panel A: Likelihood of raising a financing round				
	(1)	(2)	(3)	(4)	(5)
Post misconduct	-0.0168*	0.0049	0.0098	0.0095	0.0076
	[0.0085]	[0.0102]	[0.0067]	[0.0070]	[0.0052]
ST-SS X Post misconduct	**-0.0603*** **	**-0.0563*** **	**-0.0431*** **	**-0.0433*** **	**-0.0313*** **
	[0.0131]	**[0.0118]**	**[0.0107]**	**[0.0107]**	**[0.0086]**
ST-DS X Post misconduct	**-0.0397*** **	**-0.0389*** **	**-0.0344*** **	**-0.0346*** **	**-0.0279*** **
	[0.0108]	**[0.0114]**	**[0.0118]**	**[0.0118]**	**[0.0089]**
DT-SS X Post misconduct	**-0.0154*** **	**-0.0116*** **	**-0.0010**	**-0.0011**	**-0.0059**
	[0.0049]	**[0.0041]**	**[0.0043]**	**[0.0043]**	**[0.0048]**
Ln. Startup Age		-0.0401***	-0.0000	0.0001	-0.0058
		[0.0057]	[0.0083]	[0.0084]	[0.0067]
Constant	0.0463***	0.1106***	0.0737***	0.0754***	0.0782***
	[0.0051]	[0.0055]	[0.0147]	[0.0146]	[0.0117]
R2	109,644	109,531	109,509	109,509	90,431
Observations	0.045	0.058	0.313	0.313	0.323
	Panel B: Log of Amount Raised				
	(1)	(2)	(3)	(4)	(5)
Post misconduct	-0.2185*	0.0414	0.1192	0.1143	0.0843
	[0.1240]	[0.1452]	[0.0968]	[0.1013]	[0.0709]
ST-SS X Post misconduct	**-0.9067*** **	**-0.8476*** **	**0.6295*** **	**-0.6326*** **	**-0.4245*** **
	[0.2065]	**[0.1859]**	**[0.1633]**	**[0.1631]**	**[0.1221]**
ST-DS X Post misconduct	**-0.5535*** **	**-0.5415*** **	**-0.4749*** **	**-0.4768*** **	**-0.3643*** **
	[0.1573]	**[0.1643]**	**[0.1674]**	**[0.1670]**	**[0.1189]**
DT-SS X Post misconduct	**-0.2353*** **	**-0.1794*** **	**-0.0126**	**-0.0141**	**-0.0899**
	[0.0701]	**[0.0613]**	**[0.0672]**	**[0.0675]**	**[0.0733]**
Ln. Startup Age		-0.4917***	0.1983*	0.1963*	0.0962
		[0.0722]	[0.1079]	[0.1086]	[0.0861]
Constant	0.6433***	1.4739***	0.7752***	0.8003***	0.8510***
	[0.0762]	[0.0756]	[0.1913]	[0.1899]	[0.1519]
R2	109,644	109,531	109,509	109,509	90,431
Observations	0.043	0.055	0.325	0.325	0.338
Misconduct FE	N	N	N	Y	Y
Startup FE	N	N	Y	Y	Y
State X Year FE	N	Y	Y	Y	Y
Sector X Year FE	Y	Y	Y	Y	Y
Standard Errors	Clustered at misconduct level				

Notes: This table reports the difference-in-difference model estimating the effect of misconduct allegations on the likelihood of raising a round (Panel A) and natural logarithm of the amount raised in a year t (Panel B). Here, we construct four distinct categories to account for the overlap between innocent startups and perpetrators, namely: (a) those developing similar technology and located in same state (ST-SS), (b) those developing similar technology and located in different state (ST-DS), (c) those developing dissimilar technology and located in same state (DT-SS), and (d) those developing dissimilar technology and located in different state (DT-DS). The results of our primary variable of interest represent the difference in coefficients between the three categories (ST-SS, ST-DS, DT-SS) and our control group (DT-DS). We observe each startup over the period starting five years before a given misconduct allegation was reported for the first time in the news and ending five years after. Post-misconduct is an indicator that equals 1 in the period following the first occurrence of a misconduct allegation in the news and zero otherwise. We introduce the natural log of startup's age plus 1 to control for the startup life cycle from column (2) onwards. We progressively introduce our fixed effects starting with sector-with-year in Column (1), followed by state-with-year, startup, and misconduct level in Column (2), (3), and (4) respectively. In Column (5), we regress for the sub-sample of startups that have not been acquired. We cluster the standard errors at the misconduct level in all regressions and are reported in parentheses. Significance levels are noted as follows: * - p $<$ 0.10; ** - p $<$ 0.05; and *** - p $<$ 0.001.

Table 5: Heterogeneous effect by types of misconduct allegations

	Manageable Risk	*Unmanageable Risks*		
	Intellectual Property Infringements	Financial Fraud	Sexual Harassment	Technological Misconduct
	Panel (A): Likelihood of raising a round			
	(1)	(2)	(3)	(4)
Tech. similar startup X Post misconduct	**-0.0116**	**-0.0188*****	**-0.0411*****	**-0.0543*****
	(0.0097)	**(0.0067)**	**(0.0116)**	**(0.0154)**
R2	0.3046			
Observations	288,317			
	Panel (B): Ln. Amount Raised			
	(1)	(2)	(3)	(4)
Tech. similar startup X Post misconduct	**-0.1547**	**-0.2583*****	**-0.5856*****	**-0.8066*****
	(0.1469)	**(0.0936)**	**(0.1658)**	**(0.2429)**
R2	0.3150			
Observations	288,317			
Misconduct FE	Y			
Startup FE	Y			
State X Year FE	Y			
Sector X Year FE	Y			
Standard Errors	Clustered at misconduct level			

Notes: This table reports average effect by the type of misconduct allegations on the likelihood of raising a round (Panel A) and the logarithm of amount raised (Panel B) for the treatment group, relative to the control group. The average effects were estimated by making use of the margins command in STATA after estimating the full difference-in-difference model with the primary variable of interest being a triple interactive term: $PostMisconduct_{j,t} * Tech.SimilarStartup_{i,j} * MisconductType_i$. As with earlier regressions, the estimation was undertaken for the period starting five years before a given misconduct was reported for the first time in the news and ending five years after. We categorized the types of misconduct allegations based on description reported in the first news article. For instance, Theranos was classified as technological misconduct based on John Carreyrou's article published by the Wall Street Journal in 2015. Standard errors (in parentheses) are clustered at the misconduct level. Significance noted as: * - p $<$ 0.10; ** - p $<$ 0.05; and *** - p $<$ 0.01.

Table 6: Heterogeneous effect by ex-ante uncertainty

	Early Stage	Late-Stage
	Panel (A): Likelihood of raising a round	
	(1)	(2)
Tech. similar startup X Post misconduct	**-0.0210*** **	**-0.0041**
	[0.0065]	**[0.0211]**
R2	0.3096	
Observations	288,317	
	Panel (B): Ln. Amount Raised	
	(1)	(2)
Tech. similar startup X Post misconduct	**-0.2768*** **	**-0.1981**
	[0.0910]	**[0.3402]**
R2	0.3209	
Observations	288,317	
Misconduct FE	Y	
Startup FE	Y	
State X Year FE	Y	
Sector X Year FE	Y	
Standard Errors	Clustered at misconduct level	

Notes: This table reports average effect by different stages of innocent startups on the likelihood of raising a round (Panel A) and the logarithm of amount raised (Panel B) for the treatment group, relative to the control group. The average effects were estimated by making use of the margins command in STATA after estimating the full difference-in-difference model with the primary variable of interest being a triple interactive term: $PostMisconduct_{j,t} * Tech.SimilarStartup_{i,j} * Ex - antestage_{i,j}$. As with earlier regressions, the estimation was undertaken for the period starting five years before a given misconduct allegation was reported for the first time in the news and ending five years after. We classify innocent startups that raised beyond Series B before the misconduct allegations were reported as late-stage and those that had raised up to Series B before the misconduct allegations were reported as early-stage. Standard errors (in parentheses) are clustered at the misconduct level. Significance noted as: * - p < 0.10; ** - p < 0.05; and *** - p < 0.01.

Table 7: VCs, Prominent VCs, and Non-VCs reaction to misconduct allegations

	All Investors	VCs		Prominent VCs		Non-VCs	
	Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Misconduct	0.0228	0.0103	0.0538*	0.0036	0.0521**	0.0149	0.0299
	[0.0200]	[0.0145]	[0.0308]	[0.0087]	[0.0236]	[0.0114]	[0.0295]
Tech. similar startups X Post misconduct	**-0.0792*****	**-0.0500*****	**-0.1638*****	**-0.0410*****	**-0.1416*****	**-0.0337*****	**-0.1033****
	[0.0212]	**[0.0174]**	**[0.0568]**	**[0.0115]**	**[0.0472]**	**[0.0123]**	**[0.0448]**
Ln. startup age	0.0685***	0.0540***	0.3516***	0.0228	0.2298***	0.0275**	0.1347***
	[0.0211]	[0.0188]	[0.0347]	[0.0140]	[0.0289]	[0.0116]	[0.0477]
Constant	0.0037	-0.0054	-0.1503**	0.0250	-0.0917*	0.0001	0.1750**
	[0.0340]	[0.0275]	[0.0611]	[0.0213]	[0.0505]	[0.0224]	[0.0860]
R2	0.251	0.251	0.289	0.253	0.297	0.202	0.247
Observations	288,317	288,317	288,317	288,317	288,317	288,317	288,317
Misconduct FE	Y	Y	Y	Y	Y	Y	Y
Startup FE	Y	Y	Y	Y	Y	Y	Y
State X Year FE	Y	Y	Y	Y	Y	Y	Y
Sector X Year FE	Y	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered at misconduct level						

Notes: This table reports the results of a difference-in-differences model estimating the effect of misconduct allegations on the: likelihood of obtaining a round from a VC, prominent investors, and Non VC in year t is provided in Column (1), (3), and (5), respectively; and the log of amount raised from a VC, prominent investors, and Non VC in year t is provided in Column (2), (4), and (6), respectively. Each treatment startup is matched to control startup established during the same period to ensure a balanced sample. We define prominence by the top 500 investors based on amount invested across our entire sample of startups. Treated startups are those developing similar technologies as misconduct perpetrators, while control startups are those developing dissimilar technologies and located in a different state as the perpetrator. Post misconduct is an indicator that equals 1 in the period following the first occurrence of a misconduct allegation in the news and zero otherwise. Tech. similar startups is an indicator identifying startups that produce similar technologies as a misconduct perpetrator. Standard errors (in parentheses) are clustered at the misconduct event level. Significance noted as: *p < 0.10; **p < 0.05; ***p < 0.01.

Table 8: Unpacking the investment choices of investors by Core and Non-Core Sectors – Effect on Dummy of Round Raised

	All Investors	VCs		Prominent VCs		Non-VCs	
	Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Misconduct	0.0029**	0.0017**	0.0032	0.0008*	0.0036**	0.0013*	0.0019
	[0.0013]	[0.0008]	[0.0020]	[0.0004]	[0.0016]	[0.0007]	[0.0019]
Tech. similar startups X Post misconduct	**-0.0052*** **	**-0.0033*** **	**-0.0113*** **	**-0.0025*** **	**-0.0096*** **	**-0.0021** **	**-0.0074** **
	[0.0015]	**[0.0010]**	**[0.0037]**	**[0.0007]**	**[0.0031]**	**[0.0009]**	**[0.0029]**
Ln. startup age	0.0041***	0.0033**	0.0192***	0.0010	0.0125***	0.0014*	0.0043
	[0.0015]	[0.0014]	[0.0021]	[0.0010]	[0.0017]	[0.0008]	[0.0036]
Constant	-0.0004	-0.0012	-0.0037	0.0013	-0.0020	0.0006	0.0194***
	[0.0024]	[0.0021]	[0.0038]	[0.0017]	[0.0031]	[0.0015]	[0.0063]
R2	0.243	0.243	0.282	0.242	0.289	0.203	0.243
Observations	288,317	288,317	288,317	288,317	288,317	288,317	288,317
Misconduct FE	Y	Y	Y	Y	Y	Y	Y
Startup FE	Y	Y	Y	Y	Y	Y	Y
State X Year FE	Y	Y	Y	Y	Y	Y	Y
Sector X Year FE	Y	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered at misconduct level						

Notes: This table reports the results of a difference-in-difference model estimating the effect of misconduct events on the likelihood of obtaining a round from VCs, prominent VCs, and Non-VCs by their core and non-core sectors in year t. We define core sectors based on the participation of an investor (VC/prominent VC/Non-VC) during the ten-year period [-13,-4] before the establishment of the startups that was alleged with a misconduct. For instance, Tesla was founded in 2003 therefore the ten-year period covers all the investment that each investor participated between 1990-1999. A sector is assigned the core sector status if it constitutes more than or equal to 50 percent of investor's portfolio, based on participation in rounds, during the ten-year period. The dependent variable in Column (2) is a dummy variable of 1 if a VC had participated in a financing round that belongs to his/her core sector; and zero otherwise. We follow a similar process to generate dependent variables in Column (4) and (6) for prominent VCs and Non-VCs, respectively. The dependent variable in Column (3) is a dummy variable of 1 if a VC had participated in a financing round that belongs to his/her non-core sector, and zero otherwise. We follow a similar process to generate dependent variables in Column (3) and (5) for prominent VCs and Non-VCs, respectively. Treated startups are those developing similar technologies as misconduct perpetrators, while control startups are those developing dissimilar technologies and located in a different state as the perpetrator. Post misconduct is an indicator that equals 1 in the period following the first occurrence of a misconduct allegation in the news and zero otherwise. Tech. similar startups is an indicator identifying startups that produce similar technologies as a misconduct perpetrator. Standard errors (in parentheses) are clustered at the misconduct event level. Significance noted as: *p < 0.10; **p < 0.05; ***p < 0.01.

Table 9: Unpacking the investment choices of investors by Core and Non-Core Sectors – Log of Amount Raised

	All Investors	VCs		Prominent VCs		Non-VCs	
	Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Misconduct	0.0458**	0.0268**	0.0478	0.0123*	0.0501**	0.0202*	0.0280
	[0.0193]	[0.0123]	[0.0316]	[0.0069]	[0.0243]	[0.0111]	[0.0282]
Tech. similar startups X Post misconduct	**-0.0805*** **	**-0.0511*** **	**-0.1660*** **	**-0.0386*** **	**-0.1419*** **	**-0.0323** **	**-0.1036** **
	[0.0228]	**[0.0158]**	**[0.05722]**	**[0.0112]**	**[0.0481]**	**[0.0132]**	**[0.0439]**
Ln. startup age	0.0741***	0.0591**	0.3477***	0.0188	0.2306***	0.0261**	0.1353***
	[0.0250]	[0.0231]	[0.0337]	[0.0172]	[0.0283]	[0.0120]	[0.0473]
Constant	-0.0210	-0.0294	-0.1374**	0.0168	-0.0869*	0.0022	0.1744**
	[0.0399]	[0.0356]	[0.0592]	[0.0277]	[0.0500]	[0.0231]	[0.0855]
R2	0.246	0.245	0.290	0.243	0.296	0.202	0.247
Observations	288,317	288,317	288,317	288,317	288,317	288,317	288,317
Misconduct FE	Y	Y	Y	Y	Y	Y	Y
Startup FE	Y	Y	Y	Y	Y	Y	Y
State X Year FE	Y	Y	Y	Y	Y	Y	Y
Sector X Year FE	Y	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered at misconduct level						

Notes: This table reports the results of a difference-in-difference model estimating the effect of misconduct events on the log of amount raised from VCs, prominent VCs, and Non-VCs by their core and non-core sectors in year t. We define core sectors based on the participation of an investor (VC/prominent VC/Non-VC) during the ten-year period [-13,-4] before the establishment of the startups that was alleged with a misconduct. For instance, Tesla was founded in 2003 therefore the ten-year period covers all the investment that each investor participated between 1990-1999. A sector is assigned the core sector status if it constituted more than or equal to 50 percent of investor's portfolio, based on participation in rounds, during the ten-year period. The dependent variable in Column (2) is the log of amount raised if a VC had participated in a financing round that belongs to his/her core sector; and zero otherwise. We follow a similar process to generate dependent variables in Column (4) and (6) for prominent VCs and Non-VCs, respectively. The dependent variable in Column (3) is the log of amount raised if a VC had participated in a financing round that belongs to his/her non-core sector, and zero otherwise. We follow a similar process to generate dependent variables in Column (3) and (5) for prominent VCs and Non-VCs, respectively. Treated startups are those developing similar technologies as misconduct perpetrators, while control startups are those developing dissimilar technologies and located in a different state as the perpetrator. Post misconduct is an indicator that equals 1 in the period following the first occurrence of a misconduct allegation in the news and zero otherwise. Tech. similar startups is an indicator identifying startups that produce similar technologies as a misconduct perpetrator. Standard errors (in parentheses) are clustered at the misconduct event level. Significance noted as: *p $<$ 0.10; **p $<$ 0.05; ***p $<$ 0.01.

Table 10: Effect of misconduct on exit opportunities of innocent startups that are technologically similar to the perpetrators

	IPO/Acquisition		IPO		Acquisition	
	(1)	(2)	(3)	(4)	(5)	(6)
Post misconduct	0.0004	0.0013	0.0006	0.0002	-0.0002	0.0010
	[0.0008]	[0.0010]	[0.0005]	[0.0005]	[0.0008]	[0.0009]
Tech. similar startups X Post misconduct	**0.0012**	**0.0011**	**0.0012***	**0.0008**	**0.0001**	**0.0003**
	[0.0011]	**[0.0011]**	**[0.0006]**	**[0.0006]**	**[0.0010]**	**[0.0009]**
Ln. Startup Age	0.0049***	0.0073***	-0.0001	0.0012	0.0050***	0.0060***
	[0.0012]	[0.0012]	[0.0005]	[0.0009]	[0.0004]	[0.0011]
Ln. Cumulative Amt. Raised	0.0014***	0.0015***	0.0003***	0.0002***	0.0011***	0.0013***
	[0.0001]	[0.0001]	[0.0000]	[0.0001]	[0.0001]	[0.0001]
Constant	0.0003	-0.0042*	0.0007	-0.0010	-0.0004	-0.0032
	[0.0012]	[0.0024]	[0.0007]	[0.0017]	[0.0009]	[0.0022]
R2	0.014	0.104	0.012	0.107	0.012	0.101
Observations	288,351	288,317	288,351	288,317	288,351	288,317
Misconduct FE	N	Y	N	Y	N	Y
Startup FE	N	Y	N	Y	N	Y
State X Year FE	Y	Y	Y	Y	Y	Y
Sector X Year FE	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered at misconduct level					

Notes: This table reports the results of difference-in-differences models estimating the likelihood that startups developing similar technologies as misconduct perpetrators experience a successful exit event (IPO or acquisition) in year t (Columns 1 and 2); an IPO (Columns 3 and 4); and an acquisition (Columns 5 and 6) relative to control startups developing dissimilar technologies and located in a different state than the perpetrator. Each treatment startup is matched to control startup established during the same period to ensure a balanced sample. We control the natural logarithm of a startup's age, and the natural logarithm of the cumulative amount of funds a startup received. Our primary regressions include misconduct event, startup, state-by-year, and sector-by-year fixed effects (Columns 2, 4 and 6). Standard errors (in parentheses) are clustered at the misconduct event level. Significance noted as: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

10 Figures

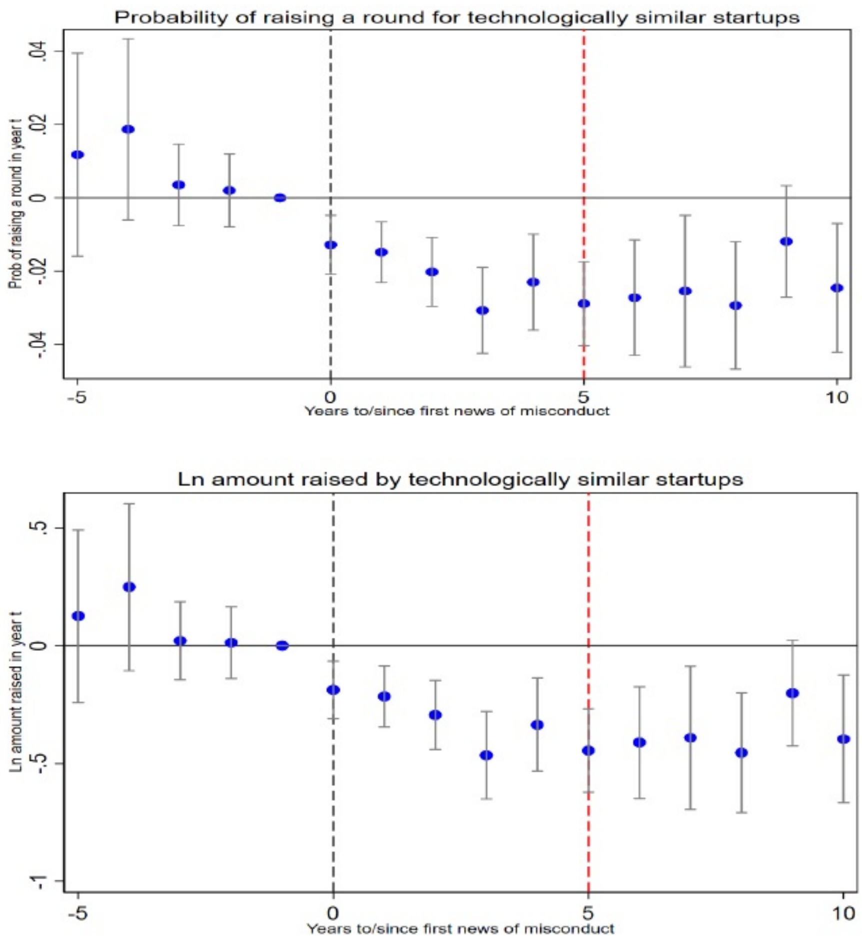

Figure 1: Effects of misconduct allegations on technologically similar startups

Notes: This figure illustrates the effect of misconduct allegations on the likelihood of raising a round and the natural logarithm of the amount raised in a year t for a startup developing similar technologies as the perpetrator relative to those developing dissimilar technologies and located in a different state. To generate these graphs, we modified our primary regression in Table 2 by substituting the post-misconduct indicator with binary variables for each of the pre- and post-treatment years. We interacted these year indicators with Tech. similar startups, which is an indicator variable identifying our treatment group. In the graphs, we report the coefficients for these interactions. The vertical bars represent 95 percent confidence intervals. The coefficient for the year immediately before the first occurrence of the news about a misconduct allegation is the baseline, therefore it is set to zero and without a confidence interval.

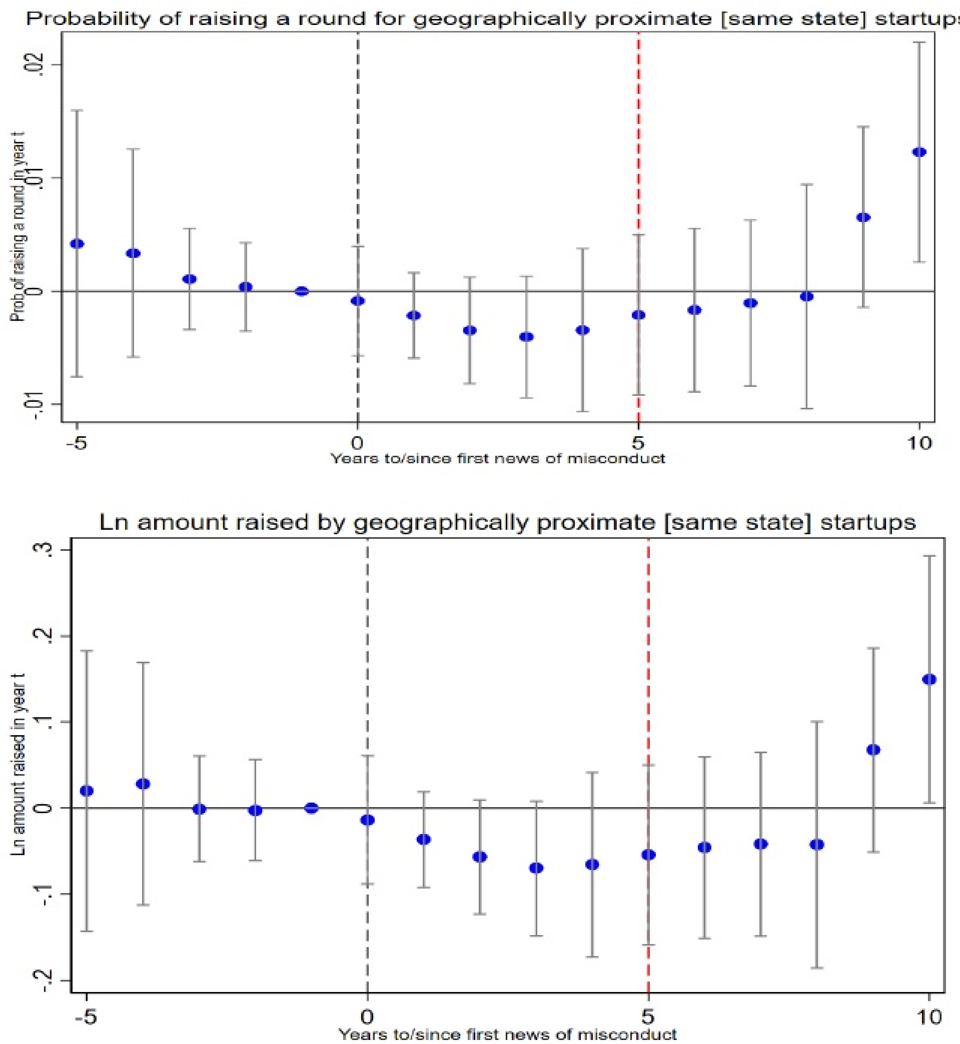

Figure 2: Effects of misconduct allegations on geographically proximate startups

Notes: This figure illustrates the effect of misconduct allegations on the likelihood of raising a round and the natural logarithm of the amount raised in a year t for a startup located in the same state as the perpetrator relative to those developing dissimilar technologies and located in a different state. To generate these graphs, we modified our primary regression in Table 4 by substituting the post-misconduct indicator with binary variables for each of the pre- and post-treatment years. We interacted these year indicators with Geo. Proximate startups, which is an indicator variable identifying our treatment group. In the graphs, we report the coefficients for these interactions. The vertical bars represent 95 percent confidence intervals. The coefficient for the year immediately before the first occurrence of the news about a misconduct allegation is the baseline, therefore it is set to zero and without a confidence interval.

11 Appendix Tables

Table A1: Details of intellectual property infringements in our sample

Sno	Startup Name	Year of Misconduct	Title of the Article
1	Netlogic Microsystems	1998	Music semiconductors files claim against NetLogic for patent infringement.
2	Emachines	1999	Compaq files suit against Emachines charging patent infringement.
3	MP3.com	1999	MP3.com sued for US$15 million by PlayMedia; PlayMedia names popular internet music site in expanding MP3 copyright suit.
4	Napster	1999	Recording Industry Group sues Napster, alleging copyright infringement on net.
5	Streambox	1999	Seattle Court issues temporary restraining order against Streambox to prevent sale and distribution of streaming technology products.
6	Scour	2000	Movie and music companies sue Internet file exchange site Scour.com.
7	Axis Systems	2001	Axis Systems responds to IKOS' patent infringement complaint.
8	Chiaro Networks	2001	VC firms, Chiaro executive hit by additional Alcatel lawsuit.
9	RLX Technologies	2001	Compaq sues RLX.
10	Good Technology	2003	Good Technology startup takes on Blackberry in wireless messaging market; Companies do battle in court over devices.
11	Three Rivers Pharmaceuticals	2003	Generic firms, Schering settle Ribavirin patent dispute.
12	Mforma Group	2006	Yahoo sues former workers, alleging trade secrets were stolen.
13	Youtube	2006	Google scrambles to 'legalize' YouTube.
14	Socializr	2007	Ticketmaster/Evite threatens Friendster founder's new website Socializr.
15	Terracycle	2007	When the worm poop hits the fan-market it; Tiny plant food brand hypes lawsuit from huge rival.
16	Fisker Automotive	2008	Maker of electric cars sues rival over trade secrets.
17	Keystone Dental	2008	Miami lawyer wins $2 million settlement in Connecticut case over dental technology; VERDICT SEARCH.
18	Project Playlist	2008	D-LISTED: Project Playlist.
19	Seeqpod	2008	D-LISTED: Project Playlist.
20	Zynga	2009	Zynga's gaming gamble.
21	Butamax Advanced Biofuels	2011	Gevo files countersuit against DuPont over isobutanol patents.
22	Gevo	2011	DUPONT JV suing GEVO for patent infringement.
23	Activecare Inc	2012	iLife Technologies files Texas patent infringement lawsuits over fall-detection technology; Company's patents allow position and movement monitoring, evaluation in industrial, consumer applications.
24	Aereo	2012	Broadcasters sue startup sending live local TV streams to NYC-area iPhones, iPads; Startup sued for putting US TV on the iPhone.
25	Nest Labs	2012	BRIEF: Nest Labs to fight Honeywell thermostat lawsuit.

26	Brightcove	2013	Dallas-based E-Commerce video leader Cinsay files suit for patent infringement; Lawsuit charges Joyus, Brightcove with infringing on interactive video technology.
27	Joyus	2013	Dallas-based E-Commerce video leader Cinsay files suit for patent infringement; Lawsuit charges Joyus, Brightcove with infringing on interactive video technology.
28	Pintrips	2013	Pinterest and Travel: A match made in social media heaven.
29	Alkeus Pharmaceuticals	2014	Alkermes sues Boston biotech startup for trademark infringement.
30	Flipt	2014	Battle over real estate website data.
31	Media Relevance	2014	Yahoo accuses ex-employee of taking patent, trade secrets to startup.
32	Salt Lake Comic Con	2014	Salt Lake, San Diego comic con feud would set precedent.
33	Hyperbranch Medical Technology	2015	Integra LifeSciences files patent infringement lawsuit against HyperBranch Medical Technology, Inc.
34	Shavelogic	2015	P&G files lawsuit against former employees for theft of trade secrets.
35	Crop Ventures	2016	Suit accuses ag tech company of reaping what others have sown.
36	Drive AI	2016	Google; Suit says engineer took secrets to Drive.ai.
37	Vidangel	2016	4 Hollywood studios sue Utah's VidAngel.
38	Xapo	2016	LifeLock; Complaint hits Startup CEO, GC over IP concealment.
39	Aurora	2017	PRESS: Tesla sues former autopilot director, alleging stolen secrets.
40	Serendipity Labs	2017	WeWork sues China co-Working rival as legal fight escalates.

Notes: This table provides details of 40 startups against which intellectual property infringements were reported in newspaper articles.

Table A2: Details of financial fraud in our sample

Sno	Startup Name	Year of Misconduct	Title of the Article
1	Rhythms Netconnections	2001	Milberg Weiss announces class action suit against Rhythms Netconnections, Inc.
2	Xango.com	2008	Utah Supreme Court considering XanGo case.
3	Mod Systems	2009	Investor sues MOD, execs.
4	Athenahealth	2010	The Pomerantz firm charges athenahealth, Inc. with securities fraud.
5	Novus Energy	2012	Suit alleges biomass firm diverted funds.
6	Savtira Corporation	2012	Savtira to liquidate.
7	Motionloft	2014	Former CEO of technology startup charged in investment scheme.
8	Kadmon	2015	N.Y. Supreme Court rejects motion to dismiss $150 million dollar action against banned ImClone founder Sam Waksal & his new biotech venture Kadmon, according to Meissner Associates.
9	Servergy	2015	APNewsBreak: Texas AG figures in federal securities probe.
10	Lendup	2016	Banks have reason for optimism in Treasury auction manipulation suit; FDIC says more have expressed interest in forming de novos.
11	Skully	2016	Bankruptcy imminent for failed Indiegogo startup Skully.
12	Wrkriot	2016	In Silicon Valley, a riveting tale of a startup's ugly collapse.
13	Outcome Health	2017	Citing whistleblower claims, top investors sue Outcome Health for fraud.
14	Pixarbio	2017	EQUITY ALERT: Rosen Law firm announces investigation of securities claims against PixarBio Corporation.
15	Revolutions Medical	2017	Medical startup executive gets probation in fraud case.
16	Tez	2017	Tezos ICO falls from grace as lawsuit gets filed.

Notes: This table provides details of 16 startups against which financial fraud were reported in either newspaper articles.

Table A3: Details of sexual harassment in our sample

Sno	Startup Name	Year of Misconduct	Title of the Article
1	Sendgrid	2013	Hackers got a woman fired by a startup after she called out sexual harassment.
2	Square	2013	Sex Scandal Forces Square COO's Resignation.
3	Github	2014	Former GitHub CEO is placed on leave.
4	Tinder	2014	Ex-Tinder executive slams company with sexual harassment suit.
5	Zillow	2014	Zillow sued for sexual harassment.
6	Boundary	2016	Atlanta man labeled a groper by tabloid feels betrayed.
7	Palantir Technologies	2016	Palantir charged with hiring bias against Asians; Data analytics firm says it plans to fight discrimination suit.
8	WeWork	2016	Labor disputes plague Bay Area company WeWork.
9	Betterworks	2017	BetterWorks CEO to step down following accusations of assault, sexual harassment.
10	Magic Leap	2017	Magic Leap sued for sex discrimination and false marketing.
11	Sofi	2017	Another Silicon Valley startup faces sexual harassment claims.
12	Thinx	2017	Thinx "She-E-O" responds to allegations of toxic workplace.
13	Transformation Group	2017	Tech evangelist Robert Scoble has resigned from his VR startup after several women accused him of sexual assault.
14	Virgin Hyperloop	2017	Shervin Pishevar steps aside at Sherpa, Hyperloop amid sexual harassment allegations.

Notes: This table provides details of 14 startups against which harassment related misconducts were reported in either newspaper articles. All the misconducts listed here are of the nature of sexual harassment; except for Palantir Technologies which was involved with non-sexual harassment (discrimination).

Table A4: Details of technological misconduct in our sample

Sno	Startup Name	Year of Misconduct	Title of the Article
1	Nebuad	2008	Web tracking company sued over privacy claims.
2	Flightcar	2013	Flightcar: San Francisco sues unruly SFO car rental startup from Santa Clara.
3	Calico Energy	2014	City of Naperville files lawsuit against Calico Energy.
4	Theranos	2015	Mega-hot biotech startup Theranos calls WSJ take-down 'baseless'.
5	Coin	2016	Coin hit by class action suit claiming 'False Advertising'.
6	Mozido	2016	The Financial Industry's Theranos?
7	Tikd	2017	Municipal court of Atlanta urges public to use caution with Tikd and similar services.

Notes: This table provides details of 7 startups against which technological misconduct allegations were reported in newspaper articles

Table A5: Details of other unethical misconducts in our sample

Sno	Startup Name	Year of Misconduct	Title of the Article
1	Ecampus.com	2000	National Association of College stores disputes more advertising claims by online-only textbook sellers.
2	Airbnb	2013	Judge rules Airbnb illegal in New York City.
3	Uber	2013	High-tech car service Uber faces more accusations; Lawsuit alleges labor law violations.
4	Retrophin	2014	LAWSUIT ALERT: The law firm of Andrews & Springer LLC announces that a lawsuit has been filed against Retrophin, Inc.
5	Doordash	2015	Three On-Demand food delivery services hit with lawsuits over worker misclassification.
6	Real Time Gaming Network	2015	Toledoan is charged in alleged conspiracy.
7	Resultly	2015	Andrew Grosso & Associates announces filing of $ 25 Million counterclaims on behalf of Resultly, LLC against QVC, Inc. and defeat of QVC's Motion for preliminary injunction.
8	Zenefits	2015	Who will win in Zenefits, ADP battle?
9	Grubhub	2016	Texas: Gig employer heartburn: Challenge to GrubHub's classification system continues.

Notes: This table provides details of 9 startups against which allegations were categorized under other unethical misconducts.

Table A6: Unpacking the investment choices of investors by alternative definition of Core and Non-Core Sectors – Effect on Dummy of Round Raised

	All Investors	VCs		Prominent VCs		Non-VCs	
	Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Misconduct	0.0015	0.0007	0.0036*	0.0003	0.0037**	0.0010	0.0021
	[0.0013]	[0.0009]	[0.0020]	[0.0005]	[0.0015]	[0.0007]	[0.0020]
Tech. similar startups X Post misconduct	**-0.0051*****	**-0.0032*****	**-0.0112*****	**-0.0026*****	**-0.0095*****	**-0.0022*****	**-0.0074****
	[0.0013]	**[0.0011]**	**[0.0037]**	**[0.0007]**	**[0.0031]**	**[0.0008]**	**[0.0029]**
Ln. startup age	0.0036***	0.0029**	0.0195***	0.0012	0.0125***	0.0015**	0.0043
	[0.0013]	[0.0011]	[0.0022]	[0.0008]	[0.0017]	[0.0007]	[0.0036]
Constant	0.0013	0.0005	-0.0046	0.0019	-0.0024	0.0004	0.0195***
	[0.0021]	[0.0016]	[0.0039]	[0.0012]	[0.0031]	[0.0014]	[0.0064]
R2	0.246	0.247	0.282	0.250	0.290	0.203	0.242
Observations	288,317	288,317	288,317	288,317	288,317	288,317	288,317
Misconduct FE	Y	Y	Y	Y	Y	Y	Y
Startup FE	Y	Y	Y	Y	Y	Y	Y
State X Year FE	Y	Y	Y	Y	Y	Y	Y
Sector X Year FE	Y	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered at misconduct level						

Notes: This table reports the results of a difference-in-difference model estimating the effect of misconduct events on the likelihood of obtaining a round from VCs, prominent VCs, and Non-VCs by their core and non-core sectors in year t. We define core sectors based on the participation of an investor (VC/prominent VC/Non-VC) during the ten-year period [-13,-4] before the establishment of the startups that was alleged with a misconduct. For instance, Tesla was founded in 2003 therefore the ten-year period covers all the investment that each investor participated between 1990-1999. A sector is assigned the core sector status if it constituted more than or equal to 50 percent of investor's portfolio, based on amount raised, during the ten-year period. The dependent variable in Column (2) is a dummy variable of 1 if a VC had participated in a financing round that belongs to his/her core sector; and zero otherwise. We follow a similar process to generate dependent variables in Column (4) and (6) for prominent VCs and Non-VCs, respectively. The dependent variable in Column (3) is a dummy variable of 1 if a VC had participated in a financing round that belongs to his/her non-core sector, and zero otherwise. We follow a similar process to generate dependent variables in Column (3) and (5) for prominent VCs and Non-VCs, respectively. Treated startups are those developing similar technologies as misconduct perpetrators, while control startups are those developing dissimilar technologies and located in a different state as the perpetrator. Post misconduct is an indicator that equals 1 in the period following the first occurrence of a misconduct allegation in the news and zero otherwise. Tech. similar startups is an indicator identifying startups that produce similar technologies as a misconduct perpetrator. Standard errors (in parentheses) are clustered at the misconduct event level. Significance noted as: *p $<$ 0.10; **p $<$ 0.05; ***p $<$ 0.01.

Table A7: Unpacking the investment choices of investors by alternative definition of Core and Non-Core Sectors – Log of Amount Raised

	All Investors	VCs		Prominent VCs		Non-VCs	
	Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector	Core Sector	Non-Core Sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Misconduct	0.0228	0.0103	0.0538*	0.0036	0.0521**	0.0149	0.0299
	[0.0200]	[0.0145]	[0.0308]	[0.0087]	[0.0236]	[0.0114]	[0.0295]
Tech. similar startups X Post misconduct	**-0.0792*****	**-0.0500*****	**-0.1638*****	**-0.0410*****	**-0.1416*****	**-0.0337*****	**-0.1033****
	[0.0212]	**[0.0174]**	**[0.0568]**	**[0.0115]**	**[0.0472]**	**[0.0123]**	**[0.0448]**
Ln. startup age	0.0685***	0.0540***	0.3516***	0.0228	0.2298***	0.0275**	0.1347***
	[0.0211]	[0.0188]	[0.0347]	[0.0140]	[0.0289]	[0.0116]	[0.0477]
Constant	0.0037	-0.0054	-0.1503**	0.0250	-0.0917*	0.0001	0.1750**
	[0.0340]	[0.0275]	[0.0611]	[0.0213]	[0.0505]	[0.0224]	[0.0860]
R2	0.251	0.251	0.289	0.253	0.297	0.202	0.247
Observations	288,317	288,317	288,317	288,317	288,317	288,317	288,317
Misconduct FE	Y	Y	Y	Y	Y	Y	Y
Startup FE	Y	Y	Y	Y	Y	Y	Y
State X Year FE	Y	Y	Y	Y	Y	Y	Y
Sector X Year FE	Y	Y	Y	Y	Y	Y	Y
Standard Errors	Clustered at misconduct level						

Notes: This table reports the results of a difference-in-difference model estimating the effect of misconduct events on the log of amount raised from VCs, prominent VCs, and Non-VCs by their core and non-core sectors in year t. We define core sectors based on the participation of an investor (VC/prominent VC/Non-VC) during the ten-year period [-13,-4] before the establishment of the startups that was alleged with a misconduct. For instance, Tesla was founded in 2003 therefore the ten-year period covers all the investment that each investor participated between 1990-1999. A sector is assigned the core sector status if it constituted more than or equal to 50 percent of investor's portfolio, based on amount raised, during the ten-year period. The dependent variable in Column (2) is the log of amount raised if a VC had participated in a financing round that belongs to his/her core sector; and zero otherwise. We follow a similar process to generate dependent variables in Column (4) and (6) for prominent VCs and Non-VCs, respectively. The dependent variable in Column (3) is the log of amount raised if a VC had participated in a financing round that belongs to his/her non-core sector, and zero otherwise. We follow a similar process to generate dependent variables in Column (3) and (5) for prominent VCs and Non-VCs, respectively. Treated startups are those developing similar technologies as misconduct perpetrators, while control startups are those developing dissimilar technologies and located in a different state as the perpetrator. Post misconduct is an indicator that equals 1 in the period following the first occurrence of a misconduct allegation in the news and zero otherwise. Tech. similar startups is an indicator identifying startups that produce similar technologies as a misconduct perpetrator. Standard errors (in parentheses) are clustered at the misconduct event level. Significance noted as: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

12 Appendix Figures

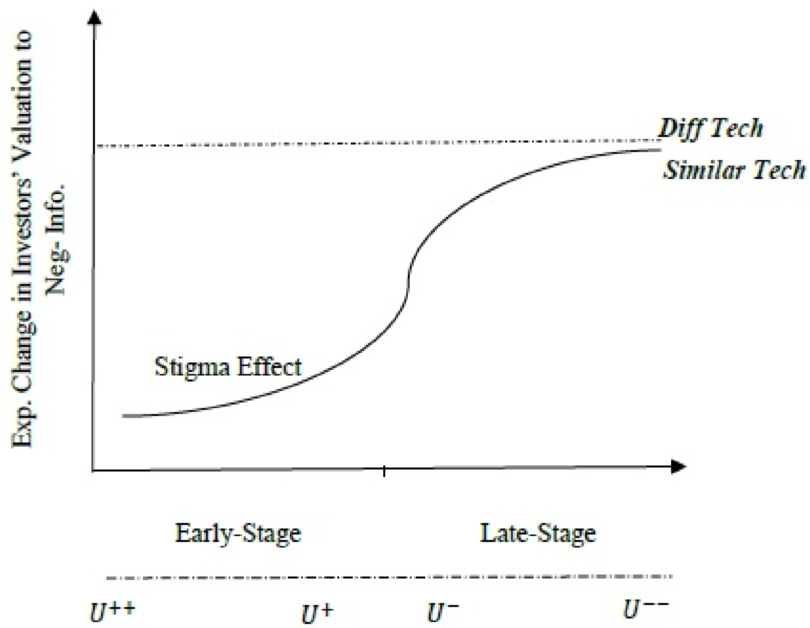

Figure A1: Expected Change in Investors Valuation owing to Misconduct Allegation

Notes: In the above figure, the x-axis represents the level of uncertainty that a startup faces at different stages of its lifecycle – early and late- stage. The y-axis represents the expected change in investors' perceptions, thereby, change in their valuation of innocent startups after a misconduct allegation is reported in the news for the first time. The dark black line represents the magnitude of change in investors valuation of innocent startups developing similar technology, as the perpetrator, after a revelation of misconduct allegation. The dotted black line represents the magnitude of change in investors valuation of innocent startups developing dissimilar technology, as the perpetrator, after a revelation of misconduct allegation. It also represents the counterfactual of expected change in investors of innocent startups without any misconduct allegation being reported in the news.

The Chilling Effect of Startup Misconduct Allegations on Investors Network

Shreekanth Mahendiran[1] and Anindya S Chakrabarti[2]

[1]HEC Lausanne

[2]Indian Institute of Management Ahmedabad

Abstract

This paper examines the evolution of investors network as a misconduct allegation against startups, they had invested in, triggers a shock to their reputation. We argue that reputational concerns both in terms of fear of loss owing to exposure to alleged startups and opportunity cost owing to a potential reduction in reputational gain expected through syndication with the tainted investor can motivate co-investors to restructure their network by distancing from the tainted investors. We employ a stacked difference-in-difference model to empirically find that co-investors substantially reduce their co-investment amount and deal size in syndications with tainted investors consequent to the revelation of misconduct allegations against startups. In addition, we find that this effect is statistically and economically significant for misconduct allegations related to technologically misleading claims and sexual harassment. We do not find any significance for misconduct allegations related to non-sexual harassment and financial fraud. Interestingly, we do not find any conclusive evidence for co-investors severing ties with the tainted investors. Taken together, our empirical results provide indicative evidence of reputational concerns altering the network dynamics of investors but resilient enough to not completely break up after a misconduct allegation revealtion.

Keywords : Entrepreneurship, Misconduct, Venture Capital, Network

1 Introduction

There is a large literature that underscores the importance of investors' networks in enhancing the entrepreneurial ecosystem (Bernstein, Giroud, & Townsend ,2016; Hochberg, Ljungqvist, & Lu ,2007; Lerner ,2022b; and others). Investor networks play a crucial role in promoting competition, investment performance, governance, and innovative activities in the entrepreneurial ecosystem (Hochberg, Ljungqvist, & Lu ,2010; Nahata ,2008; Robinson & Stuart ,2007; and others). Given this, each investor contemplates several factors in their decision to syndicate with other investors thereby developing a network to accumulate financial and non-financial resources (Hochberg, Lindsey, & Westerfield ,2015; Tian ,2012) and reduce agency conflicts (Casamatta & Haritchabalet ,2007; Hopp & Rieder ,2011).[1] However, these studies observe the investor's networks in a static manner and examine their impact on venture outcomes. There is a gap in understanding of changes in investor networks especially as new opportunities or challenges emerge and the entrepreneurial ecosystem changes over time. In addition, there has been a heightened spotlight on the role of investors and their network as high-profile misconduct allegations against startups such as FTX, Theranos, Mozido, and others have been revealed.[2]

In this paper, we explore the question of how an investor's network evolves as the shock to her reputation occurs. Hochberg et al. ,2010; Tykvová ,2007, and others have emphasized the role of investor reputation in choosing her co-investor, enforcement of contractual obligations, and developing her network structure. Most importantly, extant literature offers several potential ways in which an investor's network can evolve in response to a shock that directly affects the reputation of an investor. From Hochberg et al. ,2010; Nahata ,2008; and others, it can be argued that shock to the investor's reputation can provide an opportunity for co-investors to strategically renege on existing syndication to appropriate more reputation and economic reward, and improve their positioning within a network. Conversely, co-investors may completely overlook the reputational shock because of over-confidence in the investor's capabilities (Uzzi ,1997). Another rationale could also be that co-investors may fear incurring reputational costs by choosing to terminate the relationship with the investor experiencing reputational shock, as it could be perceived as a breach of trust by external stakeholders (Bellavitis, Rietveld, & Filatotchev ,2020). It is not apriori clear whether the investors network would change at all, and if so whether strategic behavior, reputational fear, or other factors determine the changes in an investor's network.

To answer our question, we make use of misconduct allegation against startups as the exogenous

[1] For instance, investors could choose to create new ties with another investor in their attempt to identify new and unexplored investment opportunities. Alternatively, investors could choose to break ties with another investor owing to increasing agency conflicts.

[2] Refer, for instance, to the New York Times article covering the investors role regarding Theranos misconduct.

shock to study the changes in an investor's network. The misconduct allegation against startups offers an ideal setup to investigate the change in the network as the reputation of an investor gets altered. Many studies have emphasized that investors develop a reputation based on their sorting and governance capabilities (Hochberg et al. ,2007; Yu & Kim ,2021; and others). A misconduct allegation against startups could potentially trigger revisions in expectations by other stakeholders - such as co-investors - about an investor's capabilities in identifying good entrepreneurial ventures. This, then, will allow us to capture the consequent changes to the network by observing the changes in investment amount and propensity to form syndication between the exposed investor and her co-investors.

We gathered information on misconduct allegation against startups established in the US between 1998 to 2020 from Lexis Nexis. We, then, cross-walked the identified startups to Crunchbase to collate information on their founding, investors, and financing round details. This process facilitated in identifying of 86 startups with misconduct allegations with details about the financing round - investors, amount, and timing. However, our final sample utilized for the analysis constitutes six misconduct allegation episodes against startups owing to challenges in computation and data availability. We have provided a detailed discussion that captures the transition from 86 to 6 misconduct allegations later under the data section.

To identify the causal effects of reputational shock through misconduct episodes, we estimate a stacked difference-in-difference model that assesses the change in syndication behavior at the intensive and extensive margins between co-investors and investors experiencing a reputational shock. We defined investors experiencing reputational shock owing to their direct investment in startups with misconduct allegations as *degree 0 investors*. We defined co-investors of the degree 0 investors in startups other than the alleged startups were defined as *degree 1 investor*. Then, the co-investors of degree 1 investors were defined as *degree 2 investor*. Equipped with the three sets of investors, our treatment group constitutes the syndication between degree 0 and 1 investors, and the control group constitutes the syndication between degree 2 and 1 investors. We capture the syndication behavior of degree 1 investor with degree 0 and 2 investors before and after the misconduct allegation. This allows us to attribute any difference in syndication behavior of degree 1 investor with degree 0 investors relative to degree 2 investors as the change owing to the reputational shock experienced by degree 0 investors. This also facilitates us to get an understanding of how degree 1 investors network changes as their co-investors - degree 0 investors - experience a reputational shock.

We find that degree 1 investors reduce their co-investment with degree 0 investors relative to their co-investment with degree 2 investors by 14 (in million US $) per year after the misconduct allegations are revealed. Additionally, the size of syndicated deals between degree 0 and 1 investors is much lower relative to syndicated deals between degree 2 and 1 investors - after the misconduct allegations are revealed. The negative effect on co-investments between degree 0 and 1 investors is primarily driven by misconduct allegations related to technological misleading claims, such as Theranos or Mozido, and sexual harassment, such as Zillow or Thinx, but not for allegations related to non-sexual harassment and financial fraud. Interestingly, we do not find any conclusive evidence that degree 1 investors terminate their relationship with degree 0 investors as the reputational shock occurs. Taken together, these results point towards reputational hypothesis playing a significant role in the nature of network evolution of investors over time as new challenges emerge. It appears that co-investors choose to reduce their level of co-investment with exposed investors because of two potential reasons namely (a) loss in expected reputational gain from syndicating with degree 0 investors, and (b) reputational loss of being associated with an investor tainted with investments in startups perpetrating misconducts. However, co-investors do not completely terminate the relationship with degree 0 investors as it might result in additional reputational loss through the perception of breach of trust.

We contribute to vast finance literature that examines various aspects of investor networks - especially venture capitalists - in the entrepreneurial ecosystem. This literature has focused on the conditions that determine the selection of co-investors in a syndication (Meuleman, Lockett, Manigart, & Wright ,2010; Sorenson & Stuart ,2008; Tykvová ,2007; Wang & Wang ,2012; and others). In addition, there is a huge body of research on the role of investor network in financing innovative activities (e.g. Lerner & Nanda ,2020), governance (e.g. Fracassi & Tate ,2012; Strömsten & Waluszewski ,2012), venture outcomes (e.g. Hochberg et al. ,2010; Nahata ,2008; Tian ,2012), and competition (e.g. Hochberg et al. ,2010). In this paper, we focus on how investors develop their co-investment network over time which not only experiences positive shocks such as successful exit market outcome, but negative shocks such as failures and allegations. Venugopal & Yerramilli ,2022 explores the same question in terms of positive outcomes - successful exits - in facilitating angel investors to develop their network consequently. In contrast to this, our contribution is to provide a few insights into the evolution of an investor's network as a co-investor faces reputational shock over time. We show that investors are very sensitive to negative information - even in the form of misconduct allegations - to trigger changes in co-investment with a co-investor. Another distinction is that the setup of misconduct allegations offers an opportunity to explore exogenous reputational shock rather than endogenous reputational reward that investors develop over time even adopting strategical transmission of information or termination of ventures (Chakraborty & Ewens ,2018; Grenadier, Malenko, & Strebulaev ,2014). Furthermore, by focusing on misconduct allegations as exogenous shocks, we offer a unique perspective on the resilience and adaptability of investor networks to external pressures.

We also contribute to the literature on corporate misconduct which has provided evidence of the stigmatization effect on similar firms and startups (e.g. Mahendiran ,2023; Paruchuri, Han, & Prakash ,2021; Paruchuri & Misangyi ,2015). We extend the literature by exploring whether reputational concerns trigger co-investors to restructure their network as misconduct allegations become public knowledge.

The rest of the paper is organized as follows. Section 2 presents the theoretical framework exploring syndication to develop our hypotheses. Section 3 provides a detailed discussion of the construction of the sample. Section 4 presents our empirical strategy to identify the causal effects of reputation shock on the investor's syndication behaviour. Section 5 presents the results on the co-investment amount and number of co-investors in syndicated financing deals between the treatment and control group following the revelation of a misconduct allegation. Section 6 concludes.

2 Theory and Hypotheses Development

2.1 Costs & Benefits of Syndication

An important decision for investors in undertaking investment in entrepreneurial ventures is whether to syndicate with other investors or not. This decision involves an evaluation of the tradeoff between the benefits and costs of syndication, which encompasses factors beyond the prospects of entrepreneurial ventures. Syndication allows investors to develop industry expertise, capitalize on shared resources, and diversify their portfolios (Hopp & Rieder ,2011; Tykvová ,2007). Specifically, it enhances their sorting ability, staging of financing deals, and access to broader resources that contribute to the potential success of a venture (Brander, Amit, & Antweiler ,2002; P. Gompers, Kovner, & Lerner ,2009; Lerner ,2022a; Tian ,2012). Investors could also enjoy better negotiating positions and deals with entrepreneurs as they syndicate and cooperate rather than being solo investor in the venture (Anand & Galetovic ,2000). It enhances investors' networks and reputations which can significantly influence their prospect of raising financing from limited partners and attract new entrepreneurs with innovative ventures (Hochberg et al. ,2007; Nahata ,2008; Rabi & Jeffrey ,2024; Yu & Kim ,2021).

However, it is well-documented that syndication exposes investors to coordination and agency costs owing to either the self-serving or free-riding behavior of partners (Cumming ,2006; Wright & Lockett ,2003). Trust between lead and non-lead investors can significantly affect the coordination costs and establishment of the relationship, which includes managing the informational flow between investors and entrepreneurs. Although contracts are typically adopted to determine the allocation of efforts and rewards among investors, the level of trust in lead investors can influence the agency costs incurred by non-lead investors. Meuleman, Wright, Manigart, & Lockett ,2009, theorize that opportunistic behavior by lead investors can create conditions for severe informational asymmetry with other co-investors; whereas, free-riding behavior of non-lead investors raises the potential for lapses in monitoring the venture's progress and in realizing the prospect of a successful exit market outcome. Thus, the prospect of severe coordination and agency costs, especially when considering investments in risky and innovative ventures, can affect the attractiveness of syndication.

Furthermore, Bellavitis et al. ,2020, finds that repeated syndication with the same co-investors can lead to diminishing marginal returns as overlapping processes and practices may limit network breadth and search behavior of investors to identify new and emerging ventures across different sectors. It could introduce complacency wherein co-investors might grow confident and overlook due diligence processes affecting their ability to undertake effective sorting and monitoring of ventures (Dushnitsky & Lavie ,2010; Uzzi ,1997; Zahra, Yavuz, & Ucbasaran ,2006). Bellavitis et al. ,2020, recommends investors consider an optimal mix of new and existing co-investors while considering syndication of financing deals. The presence of new co-investors could serve as a competitive mechanism wherein it incentivizes existing partners to not adopt any opportunistic or hold-up behavior to avoid being substituted with another co-investor in future prospective financing deals. Investors, thus, have to incur search costs for identifying new co-investors to continue to accrue the benefits of syndication.

2.2 Role of Reputation in Syndication

Extant literature has highlighted the role of investors' reputation in facilitating the syndication process (Gu & Lu ,2014; Plagmann & Lutz ,2019; Wright & Lockett ,2003). Trust and familiarity can play a significant role in the selection of co-investors for syndication (P. A. Gompers, Mukharlyamov, & Xuan ,2016; Mark ,1992). Investors cannot objectively observe and evaluate the skill and trustworthiness of other investors, especially given the presence of high uncertainty and informational asymmetry. Reputation, thus, could be leveraged as a proxy by other stakeholders to generate expectations about an investor which in turn can be crucial in determining their selection and the nature of the contract in a syndication.

Gu & Lu ,2014, theorize that less-established investors have a higher need to associate themselves with reputable investors thereby seeking to receive reputational, in addition to economic, gain from such syndication activities. As their reputation develops, these investors will have better opportunities to syndicate with other reputable investors which can bring greater access to private information, resources, and incentives to invest in promising and innovative ventures (Biais & Perotti ,2008; Millon & Thakor ,1985). Consequently, reputable investors experience a greater likelihood of participating in better investment opportunities and enjoy significantly higher market performances (Hochberg et al. ,2007).

Meuleman et al. ,2010, 2009, and others emphasize the role of reputation in mitigating the agency costs involved in syndication. Tykvová ,2007, develop a theoretical model wherein investors face the problem of hold-up, shirking, or opportunistic behavior by co-investors in syndication. However, co-investors fear reputational penalties being imposed by investors in the event of such opportunistic behavior. This, then, provides incentives for co-investors not to renege on their contractual obligations and undertake adequate effort in the syndication. Atanasov, Ivanov, & Litvak ,2012, finds that litigated VCs experience a significant reputational loss through reduced opportunity to participate in financing deals and the ability to raise funds from limited partners. Thus, reputational concerns can motivate investors to adhere to certain standards and become reliable partners in syndication - especially in the tightly knit and cohesive VC industry.

2.3 Consequences of Misconduct Allegation on Syndication

Investors are sensitive to information that can result in reputational loss within their existing network and affect the generation of new ties with potential co-investors in the future. Prior literature has documented that investors strategically counter any negative reports that emerge as a consequence of their action, such as opportunistic behavior, overconfidence, and others (Atanasov et al. ,2012; Tykvová ,2007; Zacharakis & Shepherd ,2001), and indirect spillovers owing to association with bad actors (Paruchuri et al. ,2021; Paruchuri & Misangyi ,2015). For instance, Grenadier et al. ,2014, theorized that investors strategically time the termination of their underperforming investments under the guise of macro shocks, such as financial crisis, to hide their true type and protect their reputation. Additionally, investors strategically delay sharing information about their underperforming investments to raise financing from limited partners Chakraborty & Ewens ,2018.

Misconduct allegations against a startup can alter the relationship between an investor and her co-investor, thereby influencing any potential syndication activity in the future. Similar to investors adopting sequential investments in ventures (Nanda & Rhodes-Kropf ,2017), each co-investor might choose to stage her co-investments with an investor as a new relationship begins. The sequential co-investment strategy relies upon the co-investor's belief that an investor can sort good ventures in addition to their ability to attract other reputable co-investors in future syndications. A co-investor will continue to participate and increase her investment in subsequent syndication as long as she continues to receive positive signals.

As the positive signal changes to a negative signal, such as the revelation of misconduct allegations, it can affect the co-investor's expectations about the reputational gain in syndicating with an investor associated with the alleged startup.[3] They might even fear reputational loss by being associated with a tainted investor (Greve, Palmer, & Pozner ,2010; Paruchuri et al. ,2021; Paruchuri & Misangyi ,2015). Additionally, misconduct allegations can trigger co-investors to revise their expectations about the tainted investor's ability to attract other reputable co-investors for future syndication. They will also alter their perception of the tainted investor's capability to sort ventures and ability to attract new entrepreneurs with innovative projects (Nahata ,2008). Consequently, it will result in co-investors incurring additional costs in investing efforts to safeguard their reputation and in attracting new investment opportunities.

Furthermore, each investor is expected to carry out a certain role - which includes efforts to monitor and guide entrepreneurs to achieve a successful exit - in syndication. Tykvová ,2007, theorizes that reputational gain ensures that each investor invests efforts to carry out this particular role. However, a co-investor might expect the tainted investor to focus their attention and efforts on dealing with the negative consequences of misconduct allegations (Ocasio ,1997). This could constrain the resources of a tainted investor. Co-investors will expect a tainted investor to shirk in their responsibilities within the syndication, thereby increasing the likelihood of losing control over the venture (P. A. Gompers ,2022). This will generate dissatisfaction among the co-investors which will affect their willingness to participate in syndications with the tainted investor (Zhelyazkov & Gulati ,2016).

In addition to the expected increase in costs and dwindling trust, the experience from prior syndication with the tainted investor will play a role in the co-investors' determination of the level of investment in future syndication after a misconduct allegation (ibid). In the case of negative prior experience, where the tainted investor had been opportunistic or underperformed, a co-investor will choose not to undertake any investment with the tainted investor in any future syndication. A co-investor will leverage the strategic opportunity to renege the syndication with the tainted investor under the guise of misconduct allegations, thereby avoiding any reputational penalty that might emanate from breaking the syndication ((Grenadier et al. ,2014).[4] On the other hand, positive prior experience could act as a buffer and motivate the co-investor to invest with the tainted investor in the future (Park & Rogan ,2019).

Another rationale is that co-investors might believe that the misconduct could have occurred without

[3]By association, we refer to the investor who had directly invested in the alleged startup before the misconduct allegation became revealed. We will refer to these investors as *tainted investors* hereon unless explicitly mentioned otherwise.

[4]We can expect the co-investor to take a similar decision in the case of absence of prior experience with the tainted investor since the costs significantly outweigh the benefits from syndication. A co-investor will explore new syndication opportunities with other reputable investors rather than operating with an increased likelihood of facing moral hazard challenges through syndication with the tainted investor.

the knowledge of the tainted investor, especially given the opportunistic behavior of entrepreneurs (Jiang, Cannella, & Jiao ,2018; Scheaf & Wood ,2022). The continuation of co-investment with the tainted investor offers an opportunity to evaluate the capability of the tainted investor yet enjoy the benefits of increased positioning in the network. At the same time, the co-investor will have a strong preference to minimize her risk exposure to the tainted investor. As a result, the co-investor will reduce the level of co-investment in future syndication with the tainted investor. Therefore, we have the following hypothesis

Hypothesis 1: The level of co-investment by each investor is more likely to reduce in future syndication with the tainted investor after misconduct allegations against a startup.

As each co-investor reduces her investment, tainted investors will face severe constraints in raising bigger financing rounds through syndication after misconduct allegations. To explain, investments in innovative ventures that might yield greater economic and reputational rewards will require higher financing rounds. When a tainted investor approaches past co-investors with such a project, there is a likelihood that the co-investor might not consider it owing to reduced trust in the tainted investor. In addition, the co-investor can steal the project from the tainted investor to either undertake solo investments or find other investors to form her syndication (Tykvová ,2007).

Even when the co-investors opt to syndicate with the tainted investor, there may be demand for a better deal with higher equity in return for lower investment. The co-investors rationale for such a demand would be that they require additional incentives to compensate for increased risk exposure to the tainted investor. Further, a better equity structure for the co-investor, thereby increasing her position, might divert the attention from the tainted investor and enable attracting other reputable investors to participate in the syndication. This leaves the tainted investor not only to expect a lower economic return from such syndication but also forces them to incur higher efforts to ensure the success of that venture to reap any reputational reward. Given this, it will be better to opt for solo investment rather than to syndicate for the tainted investor.

Having said that, tainted investors have to be strategic and participate in syndication that invests in less-risky ventures or yields sub-optimal economic rewards in periods after misconduct allegations. Such participation sends a signal to other stakeholders that they still hold enough trust and reputation over their capabilities from their co-investors. This will enable them to raise adequate financing from limited partners and explore syndication opportunities with other reputable investors. Given this, we have the following hypothesis

Hypothesis 2: The size of the financing deal through syndication is more likely to reduce for the tainted investor following a misconduct allegation against a startup.

Finally, we explore the question of whether the syndication network of tainted investors will collapse after misconduct allegations against startups. Following Hypothesis 2, it is evident that tainted investors have to participate in available syndication deals to safeguard their reputation. At the same time, tainted investors will not opt to participate in syndication with a new set of co-investors. This is because tainted investors will have to incur costs in ensuring that the new set of co-investors do not exhibit any opportunistic behavior. In addition, tainted investors face heightened exposure to reputational loss in the event the syndication with new co-investors fails to produce the expected return. Rather, they will choose to syndicate with known co-investors from prior syndicaitons after the misconduct allegations. The advantage here is that the tainted investors can generate expectations about the past co-investors actions in future syndications based on their prior experience. Therefore, they can plan their efforts to rebuild their reputation by syndicating with known co-investors rather than taking on more risk and uncertainty by syndicating with an unknown and new set of co-investors. On the side of co-investors, they will have the incentive to send a signal of being a reliable partner and not just break a relationship at the sight of first adversity (Zhelyazkov & Gulati ,2016). This will increase their own reputation and network positioning in their syndication with other investors. This leads us to the following hypothesis

Hypothesis 3: A tainted investor will continue to syndicate with known co-investors from prior experience, rather than with new set of co-investors, following a misconduct allegation against a startup.

3 Data

In this section, we describe the process undertaken to construct the final sample. We follow a similar approach as Mahendiran ,2023 to collate and categorize the misconduct allegations against startups established in the US and Cengiz, Dube, Lindner, & Zipperer ,2019, Bleiberg ,2021, and Baker, Larcker, & Wang ,2022 to construct the stacked dataset. To begin with, we make use of Lexis Nexis to gather misconduct allegations against startups in the US, employing specific keywords namely: (a) startup and lawsuit; (b) startup and allegation news; (c) startup and economic espionage; (d) startup and fraud; (e) startup and fraudulent; (f) startup and harassment; (g) startup and infringement; and (h) startup and scandal. The search yielded 572 newspaper articles and legal briefs detailing misconduct allegations against 135 US startups between 1998 and 2020. From these articles, we extracted details such as the alleged startup name, timing, and nature of the misconduct allegation, as well as the extent of media coverage for each allegation.

We used the alleged startup name sourced from the articles to map to the Crunchbase database. This process allowed us to identify 86 startups with exposure to misconduct allegations in the Crunchbase database. Following the approach outlined in Mahendiran ,2023, we categorized misconduct allegations into (a) Intellectual Property Infringements, (b) Technological misconduct, (c) Sexual Harassment, (d) Non-Sexual Harassment, (e) Financial Fraud, and (f) Other unethical misconducts. Among the 86 misconduct events, 40 were classified as intellectual property infringements, 7 as technological misconduct, 12 as sexual harassment, 2 as non-sexual harassment, 16 as financial fraud, and the remaining 9 to the residual category - other unethical misconducts. We focus on technological misconduct, sexual and non-sexual harassment, and financial fraud for constructing our sample; partly based on evidence presented in Mahendiran ,2023 and our expectation that reputation concern about the investors associated with alleged startups would emerge in allegations other than intellectual property infringements. Therefore, we have a total of 37 misconduct allegations to consider for our sample construction.

In the next stage, we consider misconduct allegations that meet two criteria: *timing* and *computation feasibility*. The *timing* criterion stipulates a minimum of four years between the establishment of the startup and the misconduct allegation, ensuring adequate periods for testing parallel trends before the misconduct allegation was reported for the first time. The *computation feasibility* criterion was introduced to address challenges related to the burgeoning size of investors' networks. Researchers pursuing network-based studies face the trade-off between the computation cost of a bigger network size and the benefit of including all the investors for analysis. While considering the entire sample would be most beneficial, it does introduce heavy computational challenges - especially the time taken - in constructing the investors' network and the variables necessary to undertake the analysis. To overcome this conundrum, we introduced this criterion to ensure the selection of misconduct allegations that facilitate sample construction with ease.

The application of the *timing* criterion yields 21 misconduct allegations which are presented in the appendix tables **A1 to A4**. Subsequently, we applied the *computation feasibility* criteria and identified 6 misconduct allegations wherein four are from technological misconduct and sexual harassment, and one each from non-sexual harassment and financial fraud allegations. Of the six identified misconduct allegations, five allegations have the highest extent of coverage through newspaper articles under each category. In sum, these six misconduct allegations are used to construct the final sample by leveraging the information available in the Crunchbase database.

As noted in Te et al. ,2023, Crunchbase contains information on the founding and financing details of startups such as the date of establishment, founding team, date of the financing round, the amount raised, name and number of investors, and others. We leverage Crunchbase to capture the investment behavior of investors associated with the alleged startup and their network over the years. Given the six misconduct allegations, we begin by identifying three investor types namely: (a) degree 0 investors, (b) degree 1 investors, and (c) degree 2 investors. We define *degree 0 investors* are those investors who had directly invested with the alleged startup before the misconduct allegation was reported in the newspaper for the first time. *Degree 1 investors* are those who syndicated with degree 0 investors in financing rounds raised by startups, other than the alleged startup. *Degree 2 investors* are those who syndicated with degree 1 investors in financing rounds raised by startups; an important criterion, here, is that these startups did not face allegations or did not receive any investments from degree 0 investors.

We operationalized this by identifying alleged startups and their investors who had invested in any financial round between the establishment of the alleged startup to the misconduct allegation being reported for the first time. Then, we observed the syndication behavior of degree 0 investors to identify degree 1 investors in startups, other than the alleged startup, between the establishment year and the misconduct allegation.[5][6] Then, we identified degree 2 investors as all those who syndicated with degree 1 investors and most importantly did not make investments in any alleged startups or other startups that did not raise investments from degree 0 investors (see Figure 1).[7]

[Insert Figure 1 here]

Next, we start to construct our treatment and control group for each of the six misconduct allegations. The treatment group is constructed by taking the entire syndication activity between degree 0 and 1 investors in any startups other than the six alleged startups. Similarly, the control group is constructed by taking the entire syndication activity by degree 1 investor with any investor, other than degree 0 investors, and in any startup, other than the six alleged startups or any startup with investment from degree 0 investors. The time period for our analysis constitutes the five years before the misconduct allegation, the year of the misconduct allegation, and four years after the misconduct allegation - a total

[5] In determining degree 1 investors, we considered only those who had not invested in any of the six alleged startups that constitute our sample. We undertake this measure to ensure that degree 1 investors constitute those with ties to degree 0 investors through syndication activity, and are not contaminated by any investment in other alleged startups. For instance, we identified 13 degree 0 investors and 225 degree 1 investors for the misconduct allegation against Theranos. Of the 225 degree 1 investors, we found that 11 were degree 0 investors in the remaining five alleged startups. Therefore, we considered 13 degree 0 investors and 214 degree 1 investors to construct the sample based on the misconduct allegation against Theranos.

[6] Refer to Appendix Table 1 for details on the number of degree 0 and 1 investors for each misconduct allegation event.

[7] Note that we do not necessarily identify degree 2 investors and track their syndication with degree 1 investors over time. We adopt this approach to overcome computational challenges. To explain, consider the example of the misconduct allegation against Theranos in 2015. In this case, there are 214 degree 1 investors who had syndicated with 6,792 degree 2 investors between 2003 [establishment year of Theranos] and 2015 [year of misconduct allegation]. We would be faced with extreme computation challenges by undertaking any attempt to construct the necessary variables for 214*6,792 investor dyads over ten years. Therefore, we considered any investor, excluding degree 0 investors, with whom degree 1 investors had syndicated in financing rounds as degree 2 investors.

of ten years.[8] Therefore, we have a balanced sample where the unit of analysis varies by investor and year for each misconduct allegation event. Finally, we appended these individual stacks to generate a stacked dataset. Our final dataset encompasses 2,292 treated and control units varying over ten-years with the total number of observations amounting to 45,584.

4 Empirical approach

The objective here is to provide causal evidence on whether misconduct allegations change the syndication activity of investors who had invested in the alleged startups. Our identification relies upon the assumption that the timing of the misconduct allegation being revealed in the newspaper for the first time would be an exogenous event to other investors - degree 1 and 2 investors. We conjecture that misconduct allegations against startups will affect degree 0 investors' syndication activity with degree 1 investors (treatment group) relative to syndication activity undertaken by degree 1 with degree 2 investors (control group). To do this, we estimate a stacked difference-in-difference model and compare, over time, the syndication by the treatment and control group. We formalize the primary econometric model in Equation (1) given below:

$$Y_{k,i,t} = \alpha + \beta_1 DummyforTreatment_{k,i} + \beta_2 DummyforPostMisconduct_{k,t} +$$
$$\beta_3 DummyforTreatment_{k,i} * DummyforPostMisconduct_{k,t} + D1SyndicationActivity_{i,t} +$$
$$\nu_k + \omega_i + \varphi_t + \varepsilon_{k,i,t} - -Equation(1)$$

$Y_{k,i,t}$ captures the outcome measures in year *t* of degree 1 investor *i* for each misconduct allegation event *k*. We developed three performance measures namely: (a) amount invested per investor[9] (in million US $), (b) total amount invested (in million US $), and (c) number of investors in a financing round for treated and control units for each misconduct allegation event. $DummyforTreatment_{k,i}$ takes the value of one for syndication between degree 0 and 1 investors representing the treatment group, and zero for syndication between degree 1 and 2 investors representing the control group. $DummyforPostMisconduct_{k,t}$ takes the values of one for five years on and after the misconduct allegation was reported for the first time in the news and zero for five years before the misconduct allegation. The coefficient of interest is β_3 cap-

[8]For instance, let us take the Theranos misconduct allegation as an example. In this case, we have 214 degree 1 investors and 13 degree 0 investors as noted earlier. The treatment sample constitutes all the syndication activity between the 214 degree 1 investors with any of the 13 degree 0 investors. The control sample constitutes all the syndication activity between 214 degree 1 investors with any other investor, other than the 13 degree 0 investors, and in any startup that neither invested in alleged startups nor received investment from degree 0 investors.

[9]Crunchbase does not capture the true amount invested by each investor. It only provides the total amount invested in a financing round raised by a startup and the number of investors participating in a financing round. We derive the amount invested per investor by dividing the total amount invested by the number of investors in a financing round raised by a startup.

turing the average change in treatment group performance, post misconduct allegation relative to the control group.

We introduce control variables and a set of fixed effects in our primary specification to alleviate any concern about unobserved heterogeneities affecting the estimation of the coefficient of interest. First, we introduce $D1SyndicationActivity_{i,t}$, measuring the level of syndication activity by degree 1 investors, to capture the relationship between outcome measures and investors' syndication pattern over time is captured explicitly, thereby ensuring that the main results do not face any confounding issues. Second, we introduce a set of fixed effects such as misconduct type (ν_k), investors (ω_i), and year (φ_t) to capture for any allegation, investor, and time-related unobserved heterogeneities. $\varepsilon_{k,i,t}$ represents the idiosyncratic error term. Finally, the primary specification is estimated with robust standard errors.

5 Results

In this section, we report the main effects of misconduct allegation revelation on the amount invested per investor (in million US $) followed by the deal size (in million US $) and the number of co-investors in syndicated financing rounds between the treatment and control group. We will refer to the syndication between degree 0 and 1 investors in financing rounds as the *treatment group*, and the syndication between degree 1 and 2 investors in financing rounds as the *control group* hereon, unless otherwise explicitly mentioned.

5.1 Effect on Amount Invested per Investor

Table 1 presents the regression results from the primary specification (specified in Equation 1) with the amount invested per investor (in million US $) in financing rounds syndicated by the treatment group, relative to the control group. In column (1), we provide the regression results from the full sample by implementing a stacked difference-in-difference estimation followed by results for each misconduct allegation event in column (2) to column (7). We also undertake event study estimation to evaluate whether the parallel trends hold and understand the magnitude of the effect of misconduct allegations throughout the period of analysis (see Figure 2).[10]

[Insert Table 1 here]

[Insert Figure 2 here]

[10]The graphical illustrations of event study estimations for each misconduct event are presented in Figure 3.

We first begin with the results from the stacked difference-in-difference estimation (see Table 1 - Column 1). We observe that each degree 1 investor reduces their investment amount by 14 (in million US $) per year, statistically significant at one percent, when they syndicate with degree 0 investors, relative to syndication with degree 2 investors, after the misconduct allegations are revealed. Our estimation satisfies the parallel trend condition as the coefficient of interest is not statistically significant during the five before the misconduct allegations are revealed (see Figure 2). Further, it becomes evident that there is an immediate reduction in the amount invested by about 4 (in million US $) by the treatment control, relative to the control group, during the year of a misconduct allegation. The negative effects appear to be persistent and intensify rapidly over the years following the misconduct allegations - with a decline in the amount invested per investor by 10 (in million US $) during the first year since the misconduct allegation and reducing up to 24 (in million US $) in the fourth year since the misconduct allegation was reported in the news for the first time. In sum, the news about misconduct allegations results in an immediate and persistent negative effect where the degree 1 investors choose to invest fewer amounts (42 percent) in syndicated financing rounds with degree 0 investors, relative to those with degree 2 investors.

[Insert Figure 3 here]

Further, the estimation results for each misconduct allegation event reveal that the negative effect varies by the type of misconduct allegation. Remember that we had classified misconduct allegations into four categories namely: (a) Technological misleading claims, (b) Sexual Harassment, (c) Non-Sexual Harassment, and (d) Financial fraud. The individual estimation results reveal that the negative effect is true in the event of misconduct allegations related to technologically misleading claims and sexual harassment being reported in the news. Under technologically misleading claims, we find that the allegations against Theranos and Mozido had resulted in the treatment group reducing the amount invested per investor by 24 and 37 (in million US $) per year, respectively, relative to the control group (see Columns 2 and 3 in Table 1). The parallel trend assumption is met in both of these cases. While the effect becomes more prominent from the third year onwards since the misconduct allegations, we find that the economic and statistical significance is much stronger in the case of Mozido relative to Theranos. Moving on, we find that the sexual harassment allegations do trigger a negative effect on the amount invested in financing rounds syndicated by the treatment group, relative to the control group. The sexual harassment allegations against Zillow and Thinx resulted in the treatment group reducing their investment amount by 25 and 3 (in million US $) per year, respectively, relative to the control group. It is evident from the magnitude of the coefficient and trends of estimated difference observed in Figure

3 that the negative effect is economically and statistically stronger for Zillow and Thinx. On the other hand, non-sexual harassment and financial fraud do not result in any statistically significant difference between the treatment and control group (see Columns 6 and 7 in Table 1). In sum, our estimation results reveal that technologically misleading claims and sexual harassment trigger a negative effect on the amount invested per investor in financing rounds syndicated by the treatment group, relative to the control group; however, there is heterogeneity in the economic significance by each case even within these two categories.

As a robustness test, we re-estimate Equation (1) by changing the year of misconduct allegation revelation and the sample of treatment and control group. We undertake this placebo estimation by revising the year of misconduct allegations by five years before its actual revelation. For instance, we change the year of misconduct allegation revelation against Mozido from 2016 to 2011 wherein the pre and post-period constitute 2006 to 2010 and 2011 to 2015, respectively. Next, we identify technologically similar startups as the alleged startup to identify a different set of degree 0 investors who had similar inclinations as the tainted investors to invest in similar technology. We map the placebo set of investors - degree 0, degree 1, and degree 2 - from the identified technologically similar startups. We, then, employ a stacked difference-in-difference estimation strategy with the placebo set of treatment and control group in addition to the placebo timing of fake misconduct allegation. While the results show a statistically significant negative coefficient, the magnitude is not economically significant in both the stacked and case-wise difference-in-difference estimations (see Appendix Table A2). In addition, we observe from the event study that the difference in the level of amount invested per investor between the treatment and control group is similar before and after the placebo year of misconduct allegation revelation (see Appendix Figure A1 and A2). In essence, the placebo estimations indicate that there was no economically significant difference between the treatment and control group following the pseudo-misconduct allegation revelation. Therefore, this provides reassurance of the estimated negative effect on the treatment group, relative to the control group, post the actual misconduct revelation.

5.2 Effect on Deal Size

Table 2 presents the regression results with the dependent variable being the total amount invested (in million US $) in financing rounds syndicated by the treatment group, relative to the control group. In column (1), we provide the regression results from the full sample by implementing a stacked difference-in-difference estimation followed by results for each misconduct allegation event in column (2) to column (7). Figure 4 illustrates the event study estimation capturing visually the variation in magnitude of the effect over the period of analysis.

[Insert Table 2 here]

[Insert Figure 4 here]

We observe that the size of the syndicated deals between degree 1 and 0 investors reduces by 70 (in million US $) per year, statistically significant at one percent, relative to those syndicated between degree 1 and 2 investors, after the misconduct allegations were revealed. From Figure 4, it is evident that the parallel trend condition is met and there is an immediate statistically significant negative effect on the treatment group after the misconduct allegations were revealed. In the subsequent years, the negative effect becomes more prominent where the syndicated deal size reduces from 28 (in million US $) during the year of misconduct allegation to about 118 (in million US $) in the fourth year since the misconduct allegation. In sum, the news about misconduct allegations results in an immediate and persistent negative effect on the size of syndicated deals by treatment group, relative to the control group.

[Insert Figure 5 here]

In addition, the individual estimations reveal that technologically misleading claims and sexual harassment result in negative effects on the treatment group, relative to the control group, whereas those related to non-sexual harassment and financial fraud are not economically significant. The deal size is both statistically and economically significant following technologically misleading claims for both Theranos and Mozido - 125 and 189 (in million US $) per year, respectively. On the other hand, we find that sexual harassment allegations against Zillow result in a larger negative effect (US$116 million per year) in comparison to Thinx (US$23 million per year). From Figure 5, it becomes apparent that the negative effect observed with Thinx is driven by the steep reduction in deal size by the treatment, relative to the control group, only in the fourth year since the misconduct allegation revelation. Therefore, it can be concluded that there exists heterogeneity in the economic significance in each case, similar to those observed in the previous sub-section, even though a negative effect prevails under technologically misleading claims and sexual harassment allegations in general.

We undertake the same placebo test where we change the timing of misconduct revelation and treatment/control group to perform robustness estimations. Reassuringly, the primary coefficient of interest is not economically significant in the stacked difference-in-difference estimation (see Column 1 - Appendix Table A3). A closer examination of the event study based on the placebo misconduct allegation reveals that there is no change in levels of deal size between the treatment and control group following the placebo misconduct allegation revelation (see Appendix Figure A4). Therefore, this finding offers reassurance in the estimated negative effect on the treatment group, relative to the control group, post the actual misconduct revelation.

5.3 Effect on Investor Network

Table 3 presents the regression results with the dependent variable being the number of co-investors in financing rounds syndicated by the treatment group, relative to the control group. The construction of the dependent variable guarantees that the number of co-investors constitutes only degree 1 and degree 0 investors in the pre-misconduct allegation period. Therefore, any change in the number of co-investors for the treatment group, relative to the control group, in the post-misconduct allegation period represents the evolution of degree 0 and degree 1 investors over the period. In column (1), we provide the regression results from the full sample by implementing a stacked difference-in-difference estimation followed by results for each misconduct allegation event in column (2) to column (7). Figure 6 illustrates the event study estimation capturing visually the variation in magnitude of the effect over the period of analysis.

[Insert Table 3 here]

[Insert Figure 6 here]

[Insert Figure 7 here]

From Table 3, we observe that the degree 0 investors syndicate with a lesser number of co-investors, relative to the control group, after the misconduct allegations are revealed (see Column 1). This negative effect appears to be driven by technologically misleading claims and sexual harassment misconduct allegations (see Columns 2 to 4 in Table 3). This could be interpreted as the collapse of the degree 0 investors network after the misconduct allegations were revealed. However, a closer examination of the trend in the estimated difference in the number of co-investors in syndicated financing deals between the treatment and control group over the period offers a complex interpretation. From Figure 6, it is clear that the parallel trend assumption is not met. In addition, it appears that the change in the co-investors network follows a downward trajectory and appears to be unaffected by the misconduct allegation revelations.

Digging deeper, we find that there is heterogeneity in the correlation between misconduct allegations and investor networks (see Figure 7). It appears that technologically misleading claims are correlated with degree 0 investors syndicating with degree 1 investors consistently over the period. This is captured by the plateauing of the estimated difference in the number of co-investors in syndicated deals between the treatment and control group after the misconduct allegations were revealed. In contrast, sexual harassment claims against Zillow intensify the downward trajectory in the number of co-investors in syndicated deals. A potential rationale for this intensification could be heightened fear of reputational loss for any co-investor associated with degree 0 investors who are associated with a startup alleged with sexual harassment. This could have resulted in degree 1 investor's decision to dissociate themselves from degree 0 investors to safeguard their reputation. Moving on, we do not observe any discernable trend concerning misconduct allegations involving non-sexual harassment and financial fraud.

In sum, we cannot conclusively offer any causal interpretations of the effect of misconduct allegations on the investors' network. There is correlational evidence of investors' network stabilizing in case of technologically misleading claims that affect the capability reputation of degree 0 investors, and collapse of the network in the case of sexual harassment triggering damage to the character reputation of the degree 0 investors.[11]

6 Conclusions

In this paper, we explore the dynamics of investor networks as reputational shocks triggered by misconduct allegations against startups occur. We leverage hand-collected information about misconduct allegations against startups established in the US to construct a novel dataset comprising tainted investors - exposed to alleged startups through direct investment - and their co-investors. Employing a stacked difference-in-difference model, we investigated how investors strategically adjust their syndication behavior following such negative shocks. Our findings reveal that investors indeed react to reputational shocks, albeit not by completely terminating ties with the tainted investor. Instead, they strategically reduce their co-investment amount and size of the deal in syndicated financing deals with the tainted investor after a misconduct allegation. This reduction in co-investment signifies a cautious response, driven by concerns over potential reputational damage and the perceived loss in expected gains from syndication. Moreover, our research highlights the nuanced nature of investor responses to different types of misconduct allegations. While technologically misleading claims and sexual harassment allegations negatively influence syndication behavior, other types such as non-sexual harassment and financial fraud allegations show less pronounced effects. This suggests that the nature and severity of the misconduct allegation play a crucial role in shaping investor decisions within networks. Moving forward, our research opens avenues for further exploration, including the mechanisms through which reputational shocks propagate within networks and the long-term implications for investor strategies and startup suc-

[11] We undertake the placebo tests similar to those undertaken for the other two dependent variables. The results from these regressions are provided in Appendix Table A4 and Appendix Figures 5 and 6.

cess. By delving deeper into these areas, future studies can continue to advance our understanding of the intricate interplay between reputation, networks, and entrepreneurial outcomes.

References

Anand, B. N., & Galetovic, A. (2000). Information, nonexcludability, and financial market structure. *The Journal of Business*, *73*(3), 357–402.

Atanasov, V., Ivanov, V., & Litvak, K. (2012). Does reputation limit opportunistic behavior in the vc industry? evidence from litigation against vcs. *The Journal of Finance*, *67*(6), 2215–2246.

Baker, A. C., Larcker, D. F., & Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, *144*(2), 370–395.

Bellavitis, C., Rietveld, J., & Filatotchev, I. (2020). The effects of prior co-investments on the performance of venture capitalist syndicates: A relational agency perspective. *Strategic Entrepreneurship Journal*, *14*(2), 240–264.

Bernstein, S., Giroud, X., & Townsend, R. R. (2016). The impact of venture capital monitoring. *The Journal of Finance*, *71*(4), 1591–1622.

Biais, B., & Perotti, E. (2008). Entrepreneurs and new ideas. *The RAND Journal of Economics*, *39*(4), 1105–1125.

Bleiberg, J. (2021). Stackedev: Stata module to implement stacked event study estimator.

Brander, J. A., Amit, R., & Antweiler, W. (2002). Venture-capital syndication: Improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy*, *11*(3), 423–452.

Casamatta, C., & Haritchabalet, C. (2007). Experience, screening and syndication in venture capital investments. *Journal of financial intermediation*, *16*(3), 368–398.

Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, *134*(3), 1405–1454.

Chakraborty, I., & Ewens, M. (2018). Managing performance signals through delay: Evidence from venture capital. *Management Science*, *64*(6), 2875–2900.

Cumming, D. J. (2006). The determinants of venture capital portfolio size: empirical evidence. *The Journal of Business*, *79*(3), 1083–1126.

Dushnitsky, G., & Lavie, D. (2010). How alliance formation shapes corporate venture capital investment in the software industry: A resource-based perspective. *Strategic Entrepreneurship Journal*, *4*(1), 22–48.

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

Gompers, P., Kovner, A., & Lerner, J. (2009). Specialization and success: Evidence from venture capital. *Journal of Economics & Management Strategy*, *18*(3), 817–844.

Gompers, P. A. (2022). Optimal investment, monitoring, and the staging of venture capital. In *Venture capital* (pp. 285–313). Routledge.

Gompers, P. A., Mukharlyamov, V., & Xuan, Y. (2016). The cost of friendship. *Journal of Financial Economics*, *119*(3), 626–644.

Grenadier, S. R., Malenko, A., & Strebulaev, I. A. (2014). Investment busts, reputation, and the temptation to blend in with the crowd. *Journal of Financial Economics*, *111*(1), 137–157.

Greve, H. R., Palmer, D., & Pozner, J.-E. (2010). Organizations gone wild: The causes, processes, and consequences of organizational misconduct. *The Academy of Management Annals*, *4*(1), 53–107.

Gu, Q., & Lu, X. (2014). Unraveling the mechanisms of reputation and alliance formation: A study of venture capital syndication in china. *Strategic Management Journal*, *35*(5), 739–750.

Hochberg, Y. V., Lindsey, L. A., & Westerfield, M. M. (2015). Resource accumulation through economic ties: Evidence from venture capital. *Journal of Financial Economics*, *118*(2), 245–267.

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. (2007). Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, *62*(1), 251–301.

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. (2010). Networking as a barrier to entry and the competitive supply of venture capital. *The Journal of Finance*, *65*(3), 829–859.

Hopp, C., & Rieder, F. (2011). What drives venture capital syndication? *Applied Economics*, *43*(23), 3089–3102.

Jiang, H., Cannella, A. A., & Jiao, J. (2018). Does desperation breed deceiver? a behavioral model of new venture opportunism. *Entrepreneurship Theory and Practice*, *42*(5), 769–796.

Khanna, N., & Mathews, R. D. (2022). Skill versus reliability in venture capital. *Journal of Financial Economics*, *145*(2), 41–63.

Lawler, E. J., & Yoon, J. (1998). Network structure and emotion in exchange relations. *American sociological review*, 871–894.

Lerner, J. (2022a). The syndication of venture capital investments. In *Venture capital* (pp. 207–218). Routledge.

Lerner, J. (2022b). Venture capitalists and the oversight of private firms. In *Venture capital* (pp. 267–284). Routledge.

Lerner, J., & Nanda, R. (2020). Venture capital's role in financing innovation: What we know and how much we still need to learn. *Journal of Economic Perspectives*, *34*(3), 237–261.

Mahendiran, S. (2023). Silence of the lambs: The effects of misconduct on entrepreneurial venture outcomes. *Available at SSRN*.

Mark, G. (1992). Problems of explanation in economic sociology. *Networks and organizations: Structure, form, and action*, 25–56.

Meuleman, M., Lockett, A., Manigart, S., & Wright, M. (2010). Partner selection decisions in interfirm collaborations: The paradox of relational embeddedness. *Journal of Management Studies*, *47*(6), 995–1019.

Meuleman, M., Wright, M., Manigart, S., & Lockett, A. (2009). Private equity syndication: Agency costs, reputation and collaboration. *Journal of Business Finance & Accounting*, *36*(5-6), 616–644.

Millon, M. H., & Thakor, A. V. (1985). Moral hazard and information sharing: A model of financial information gathering agencies. *The Journal of Finance*, *40*(5), 1403–1422.

Nahata, R. (2008). Venture capital reputation and investment performance. *Journal of financial economics*, *90*(2), 127–151.

Nanda, R., & Rhodes-Kropf, M. (2017). Financing risk and innovation. *Management Science*, *63*(4), 901–918.

Ocasio, W. (1997). Towards an attention-based view of the firm. *Strategic management journal*, *18*(S1), 187–206.

Park, B., & Rogan, M. (2019). Capability reputation, character reputation, and exchange partners' reactions to adverse events. *Academy of Management Journal*, *62*(2), 553–578.

Paruchuri, S., Han, J.-H., & Prakash, P. (2021). Salient expectations? incongruence across capability and integrity signals and investor reactions to organizational misconduct. *Academy of Management Journal*, *64*(2), 562–586.

Paruchuri, S., & Misangyi, V. F. (2015). Investor perceptions of financial misconduct: The heterogeneous contamination of bystander firms. *Academy of Management Journal*, *58*(1), 169–194.

Plagmann, C., & Lutz, E. (2019). Beggars or choosers? lead venture capitalists and the impact of reputation on syndicate partner selection in international settings. *Journal of Banking & Finance*, *100*, 359–378.

Rabi, R., & Jeffrey, P. S. (2024). Deal referrals and fund strategy in venture-capital networks. *Working paper*.

Robinson, D. T., & Stuart, T. E. (2007). Network effects in the governance of strategic alliances. *The Journal of Law, Economics, & Organization*, *23*(1), 242–273.

Scheaf, D. J., & Wood, M. S. (2022). Entrepreneurial fraud: A multidisciplinary review and synthesized framework. *Entrepreneurship Theory and Practice*, *46*(3), 607–642.

Sorenson, O., & Stuart, T. E. (2008). Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks. *Administrative Science Quarterly*, *53*(2), 266–294.

Strömsten, T., & Waluszewski, A. (2012). Governance and resource interaction in networks. the role of venture capital in a biotech start-up. *Journal of Business Research*, *65*(2), 232–244.

Te, Y.-F., Wieland, M., Frey, M., Pyatigorskaya, A., Schiffer, P., & Grabner, H. (2023). Making it into a successful series a funding: An analysis of crunchbase and linkedin data. *The Journal of Finance and Data Science*, 100099.

Tian, X. (2012). The role of venture capital syndication in value creation for entrepreneurial firms. *Review of Finance*, *16*(1), 245–283.

Tykvová, T. (2007). Who chooses whom? syndication, skills and reputation. *Review of Financial Economics*, *16*(1), 5–28.

Uzzi, B. (1997). Social structure and competition in interfirm networks... *Administrative Science Quarterly*, *42*(1), 37–69.

Venugopal, B., & Yerramilli, V. (2022). Seed-stage success and growth of angel co-investment networks. *The Review of Corporate Finance Studies*, *11*(1), 169–210.

Wang, L., & Wang, S. (2012). Endogenous networks in investment syndication. *Journal of Corporate Finance*, *18*(3), 640–663.

Wright, M., & Lockett, A. (2003). The structure and management of alliances: syndication in the venture capital industry. *Journal of management studies*, *40*(8), 2073–2102.

Yu, H., & Kim, T. (2021). The effects of status on the performance of portfolio diversification strategies. *Journal of Strategy and Management*, *14*(2), 246–258.

Zacharakis, A. L., & Shepherd, D. A. (2001). The nature of information and overconfidence on venture capitalists' decision making. *Journal of business venturing*, *16*(4), 311–332.

Zahra, S. A., Yavuz, R. I., & Ucbasaran, D. (2006). How much do you trust me? the dark side of relational trust in new business creation in established companies. *Entrepreneurship theory and practice*, *30*(4), 541–559.

Zhelyazkov, P. I., & Gulati, R. (2016). After the break-up: The relational and reputational consequences of withdrawals from venture capital syndicates. *Academy of Management Journal*, *59*(1), 277–301.

7 Tables

Table 1: Effect of misconduct allegation on the amount invested per investor (in million US $) in syndicated financing rounds

Ind. Variable	Overall	Technological misleading claims		Sexual Harassment		Non-Sexual Harassment	Financial
		Theranos	Mozdio	Zillow	Thinx	Tesla	AthenaHealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Treatment	-12.554***	-16.801***	-14.463***	-9.724***	-2.791***	-12.978***	-13.408***
	(0.526)	(2.952)	(1.606)	(1.145)	(0.331)	(0.738)	(0.458)
Dummy for Treatment* Dummy for Post Misconduct Allegation	**-14.393*****	**-24.004*****	**-37.066*****	**-25.092*****	**-3.743*****	**1.365**	**0.352**
	(1.458)	**(6.119)**	**(5.074)**	**(4.072)**	**(0.725)**	**(0.942)**	**(0.750)**
Degree 1 Investors Syndication Activity	0.738***	0.884**	0.789***	1.773***	0.103**	1.166***	1.328***
	(0.112)	(0.384)	(0.179)	(0.486)	(0.044)	(0.135)	(0.182)
Constant	11.746***	20.691***	26.328***	7.839**	2.481***	7.847***	6.899***
	(1.006)	(2.896)	(2.069)	(3.223)	(0.951)	(0.684)	(0.926)
Observations	45,584	4,280	8,680	9,880	2,304	9,860	10,580
R-square	0.204	0.229	0.211	0.188	0.391	0.311	0.431
Fixed Effects							
Misconduct Type	Yes	No	No	No	No	No	No
Degree 1 Investors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the difference-in-difference model estimating the effect of misconduct allegation events on the amount invested per investor (in million US $) in syndicated financing rounds between degree 0 and degree 1 investors relative to those between degree 1 and degree 2 investors. We observed the syndicated financing rounds by degree 1 investors with degree 0 and degree 2 investors five years before a given misconduct event was reported for the first time in the news and ending five years after. Dummy for Treatment is an indicator variable that equals one for syndicated financing rounds between degree 0 and 1 investors; and zero for syndicated financing rounds between degree 1 and 2 investors. Degree 1 Investors Syndication Activity captures the level of syndication activity by degree 1 investors in a particular year t. Robust standard errors are provided in parentheses and significance levels are noted as follows: * - $p < 0.10$; ** - $p < 0.05$, and *** - $p < 0.001$.

Table 2: Effect of misconduct allegation on the total amount invested (in million US $) in syndicated financing rounds

Ind. Variable	Overall	Technological misleading claims		Sexual Harassment		Non-Sexual Harassment	Financial
		Theranos	Mozdio	Zillow	Thinx	Tesla	AthenaHealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Treatment	-44.711***	-62.138***	-43.006***	-30.327**	-11.854***	-50.494***	-53.413***
	(2.148)	(11.196)	(6.721)	(4.764)	(1.709)	(3.185)	(1.772)
Dummy for Treatment* Dummy for Post Misconduct Allegation	**-70.378*****	**-125.387*****	**-189.008*****	**-115.477*****	**-22.859*****	**8.019****	**5.166***
	(5.882)	**(27.591)**	**(19.212)**	**(16.702)**	**(4.890)**	**(3.721)**	**(2.845)**
Degree 1 Investors Syndication Activity	3.332***	4.083***	3.659***	7.664***	0.637***	4.572***	5.102***
	(0.482)	(1.747)	(0.728)	(2.114)	(0.307)	(0.470)	(0.590)
Constant	50.436***	88.750***	118.590***	29.549**	9.807	31.882***	28.101***
	(4.108)	(12.585)	(8.911)	(14.174)	(6.538)	(2.432)	(2.955)
Observations	45,584	4,280	8,680	9,880	2,304	9,860	10,580
R-square	0.219	0.227	0.243	0.198	0.343	0.309	0.439
Fixed Effects							
Misconduct Type	Yes	No	No	No	No	No	No
Degree 1 Investors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the difference-in-difference model estimating the effect of misconduct allegation events on the total amount invested (in million US $) in syndicated financing rounds between degree 0 and degree 1 investors relative to those between degree 1 and degree 2 investors. We observed the syndicated financing rounds by degree 1 investors with degree 0 and degree 2 investors five years before a given misconduct event was reported for the first time in the news and ending five years after. Dummy for Treatment is an indicator variable that equals one for syndicated financing rounds between degree 0 and 1 investors; and zero for syndicated financing rounds between degree 1 and 2 investors. Degree 1 Investors Syndication Activity captures the level of syndication activity by degree 1 investors in a particular year t. Robust standard errors are provided in parentheses and significance levels are noted as follows: * - $p < 0.10$; ** - $p < 0.05$, and *** - $p < 0.001$.

Table 3: Effect of misconduct allegation on number of co-investors in syndicated financing rounds

Ind. Variable	Overall	Technological misleading claims		Sexual Harassment		Non-Sexual Harassment	Financial
		Theranos	Mozdio	Zillow	Thinx	Tesla	AthenaHealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Treatment	-12.823***	-13.854***	-18.276***	-9.702***	-25.502***	-11.005***	-10.086***
	(0.246)	(0.997)	(0.776)	(0.331)	(2.697)	(0.298)	(0.272)
Dummy for Treatment* Dummy for Post Misconduct Allegation	**-6.013*****	**-11.519*****	**-10.790*****	**-13.513*****	**-6.892**	**2.217*****	**0.296**
	(0.437)	**(1.769)**	**(1.303)**	**(0.791)**	**(4.302)**	**(0.407)**	**(0.415)**
Degree 1 Investors Syndication Activity	0.743***	0.574***	0.782***	1.060***	0.593*	1.003***	0.986***
	(0.138)	(0.196)	(0.182)	(0.147)	(0.352)	(0.087)	(0.093)
Constant	9.307***	14.735***	15.973***	8.099***	15.999**	5.737***	5.528***
	(1.244)	(1.934)	(2.098)	(1.248)	(7.483)	(0.440)	(0.475)
Observations	45,584	4,280	8,680	9,880	2,304	9,860	10,580
R-square	0.493	0.497	0.503	0.529	0.477	0.542	0.545
Fixed Effects							
Misconduct Type	Yes	No	No	No	No	No	No
Degree 1 Investors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the difference-in-difference model estimating the effect of misconduct allegation events on the number of co-investors in syndicated financing rounds between degree 0 and degree 1 investors relative to those between degree 1 and degree 2 investors. We observed the syndicated financing rounds by degree 1 investors with degree 0 and degree 2 investors five years before a given misconduct event was reported for the first time in the news and ending five years after. Dummy for Treatment is an indicator variable that equals one for syndicated financing rounds between degree 0 and 1 investors; and zero for syndicated financing rounds between degree 1 and 2 investors. Degree 1 Investors Syndication Activity captures the level of syndication activity by degree 1 investors in a particular year t. Robust standard errors are provided in parentheses and significance levels are noted as follows: * - $p < 0.10$; ** - $p < 0.05$, and *** - $p < 0.001$.

8 Figures

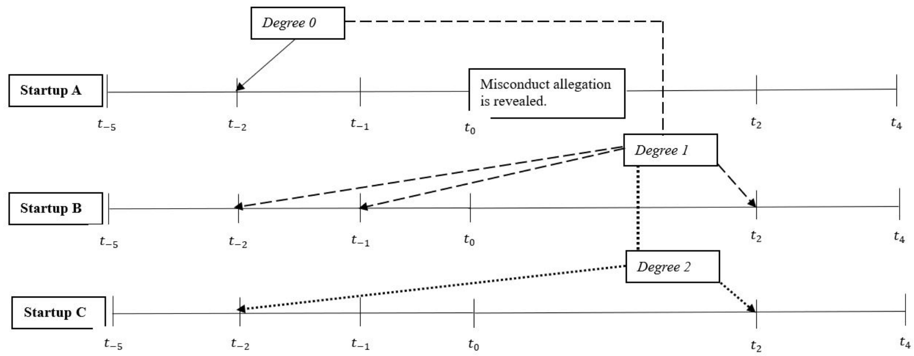

Figure 1: Illustration of the approach adopted to construct the sample

Notes: This figure illustrates the steps undertaken to identify the three types of investors: degree 0, 1, and 2 investors; thereupon construction of the sample containing treatment and control group. In the illustrated example, there are three startups - A, B, and C. Let us assume that they were established in the same year - which is five years before a misconduct allegation is reported for the first time [represented as t_{-5} above]. *Startup A* is alleged with a misconduct allegation at t_0, whereas Startup B and C do not face any misconduct allegation at all. We observe that there is an investor who had directly invested in Startup A, the alleged startup, in t_{-2}. We categorize this investor as a degree 0 investor. We also observe that degree 0 investor syndicated with another investor to invest in two financing rounds raised by Startup B [represented in dashed lines above]. These investments take place in periods - t_{-2} and t_{-1} - before the misconduct allegation against Startup A was revealed. We categorize the co-investor of degree 0 investor in Startup B as degree 1 investor. The syndication between degree 0 and degree 1 investor in Startup B constitutes our treatment group - wherein we observe their syndication activity five before and after the misconduct allegation against Startup A. Moving on, we observe that degree 1 investor syndicates with another investor in period t_{-2} to invest in Startup C - which neither experiences any misconduct allegation nor investment from degree 0 investor since its establishment. We categorize this co-investor of degree 1 investor as degree 2 investor. The syndication activity between degree 1 and 2 investors, represented in dotted lines above, constitute the control group which we observe for the period five years before and after the misconduct allegation.

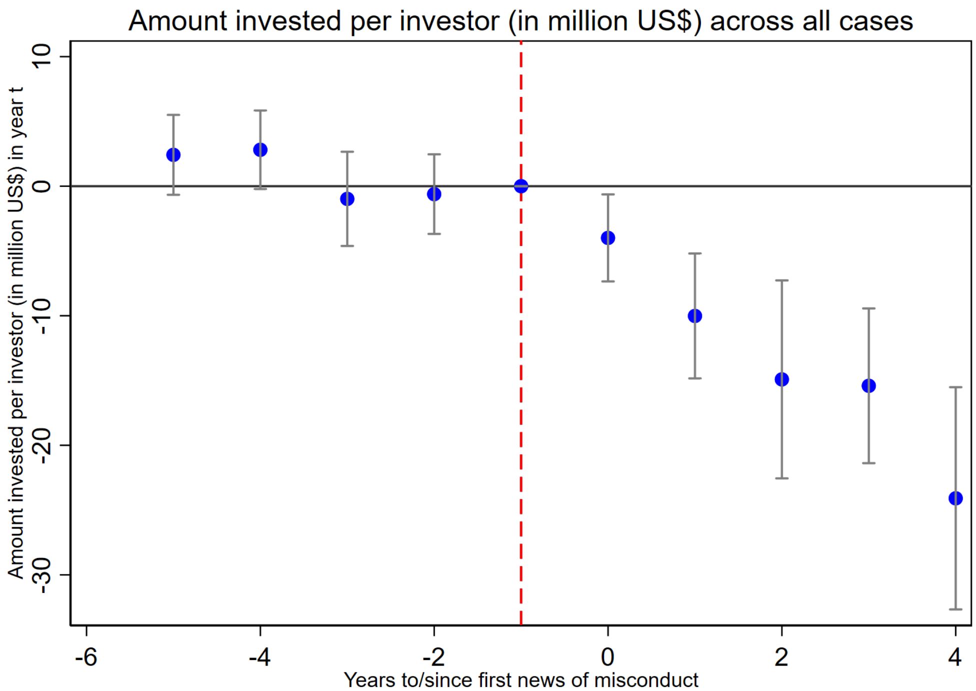

Figure 2: Effect of misconduct allegations on the amount invested per investor (in million US $) in syndicated financing rounds

Notes: This figure represents the event study estimating the effect of misconduct events on the amount invested per investor (in million US $) in syndicated financing rounds between degree 0 and degree 1 investors relative to those between degree 1 and degree 2 investors. We observed the syndicated financing round by degree 1 investors with degree 0 and degree 2 investors five years before a given misconduct event was reported for the first time in the news and ending five years after. The red dashed line marks the year before the misconduct allegation was reported for the first time in the news. It is the base period for estimating the difference-in-difference between the treatment and control group for the period after the misconduct allegation relative to the period before.

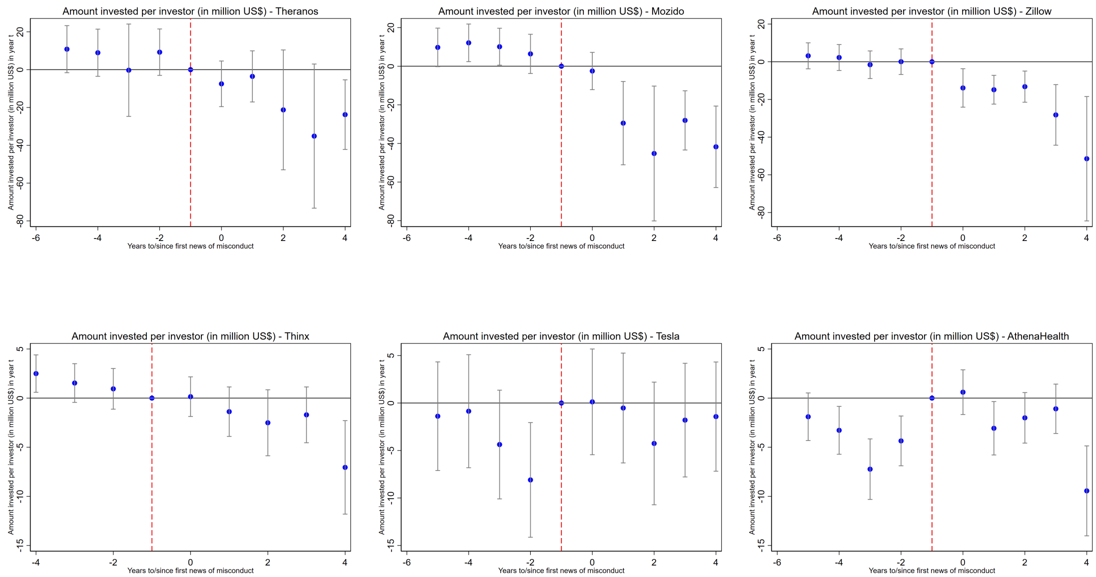

Figure 3: Effect of misconduct allegations on the amount invested per investor (in million US $) in syndicated financing rounds by each case

Notes: This figure represents the event study estimating the effect of misconduct events on the amount invested per investor (in million US $) in syndicated financing rounds between degree 0 and degree 1 investors relative to those between degree 1 and degree 2 investors for each of the six cases. We observed the syndicated financing round by degree 1 investors with degree 0 and degree 2 investors five years before a given misconduct event was reported for the first time in the news and ending five years after. The red dashed line marks the year before the misconduct allegation was reported for the first time in the news. It is the base period for estimating the difference-in-difference between the treatment and control group for the period after the misconduct allegation relative to the period before.

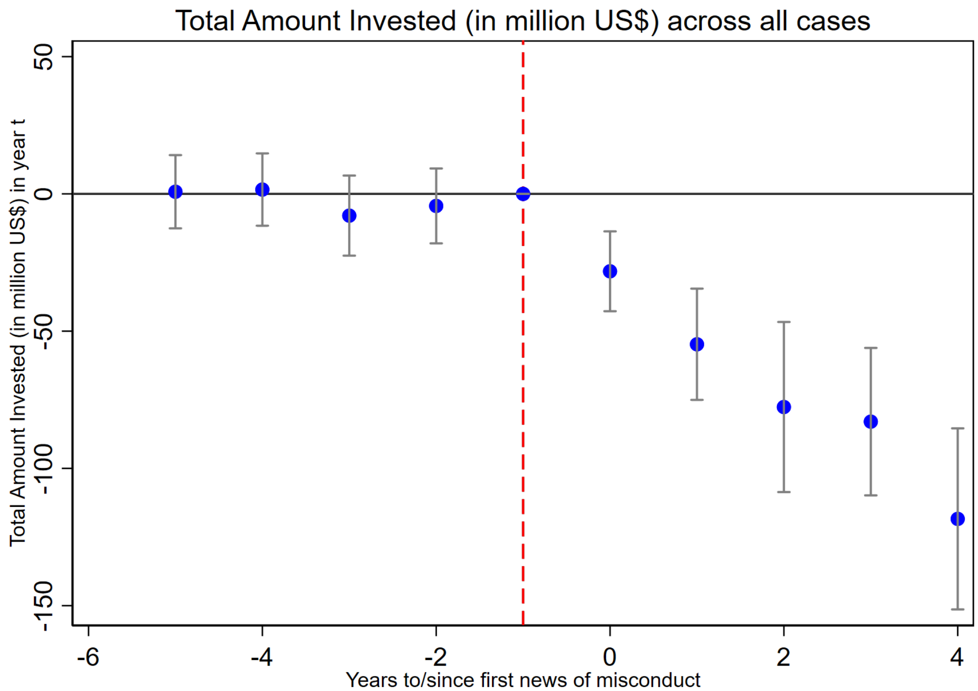

Figure 4: Effect of misconduct allegations on the total amount invested (in million US $) in syndicated financing rounds

Notes: This figure represents the event study estimating the effect of misconduct events on the total amount invested (in million US $) in syndicated financing rounds between degree 0 and degree 1 investors relative to those between degree 1 and degree 2 investors. We observed the syndicated financing round by degree 1 investors with degree 0 and degree 2 investors five years before a given misconduct event was reported for the first time in the news and ending five years after. The red dashed line marks the year before the misconduct allegation was reported for the first time in the news. It is the base period for estimating the difference-in-difference between the treatment and control group for the period after the misconduct allegation relative to the period before.

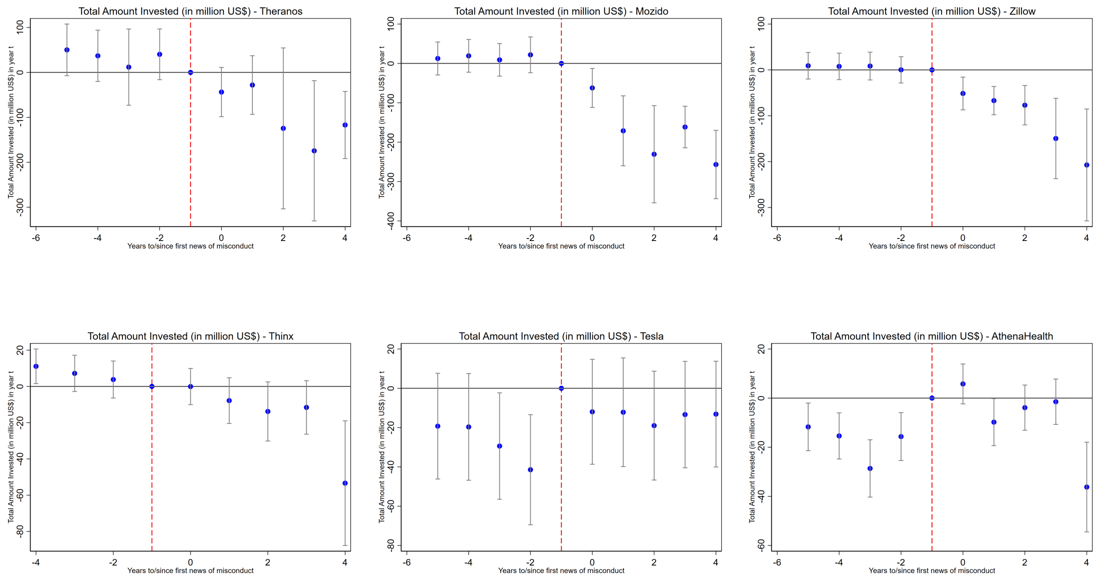

Figure 5: Effect of misconduct allegations on the total amount invested (in million US $) in syndicated financing rounds by each case

Notes: This figure represents the event study estimating the effect of misconduct events on the total amount invested (in million US $) in syndicated financing rounds between degree 0 and degree 1 investors relative to those between degree 1 and degree 2 investors for each of the six cases. We observed the syndicated financing round by degree 1 investors with degree 0 and degree 2 investors five years before a given misconduct event was reported for the first time in the news and ending five years after. The red dashed line marks the year before the misconduct allegation was reported for the first time in the news. It is the base period for estimating the difference-in-difference between the treatment and control group for the period after the misconduct allegation relative to the period before.

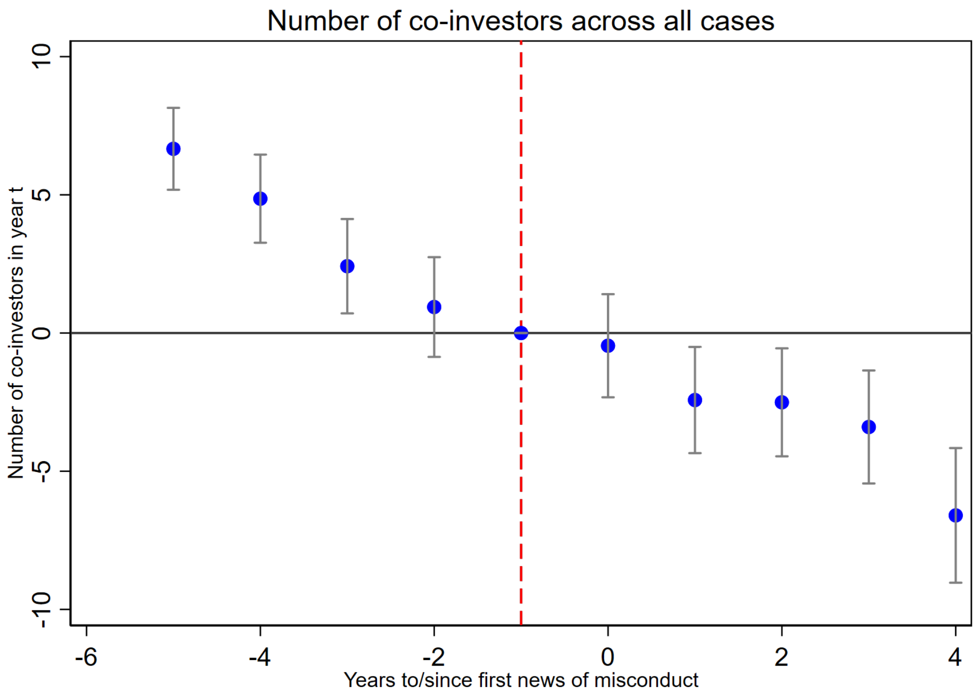

Figure 6: Effect of misconduct allegations on the number of co-investors in syndicated financing rounds
Notes: This figure represents the event study estimating the effect of misconduct events on the number of co-investors in syndicated financing rounds between degree 0 and degree 1 investors relative to those between degree 1 and degree 2 investors. We observed the syndicated financing round by degree 1 investors with degree 0 and degree 2 investors five years before a given misconduct event was reported for the first time in the news and ending five years after. The red dashed line marks the year before the misconduct allegation was reported for the first time in the news. It is the base period for estimating the difference-in-difference between the treatment and control group for the period after the misconduct allegation relative to the period before.

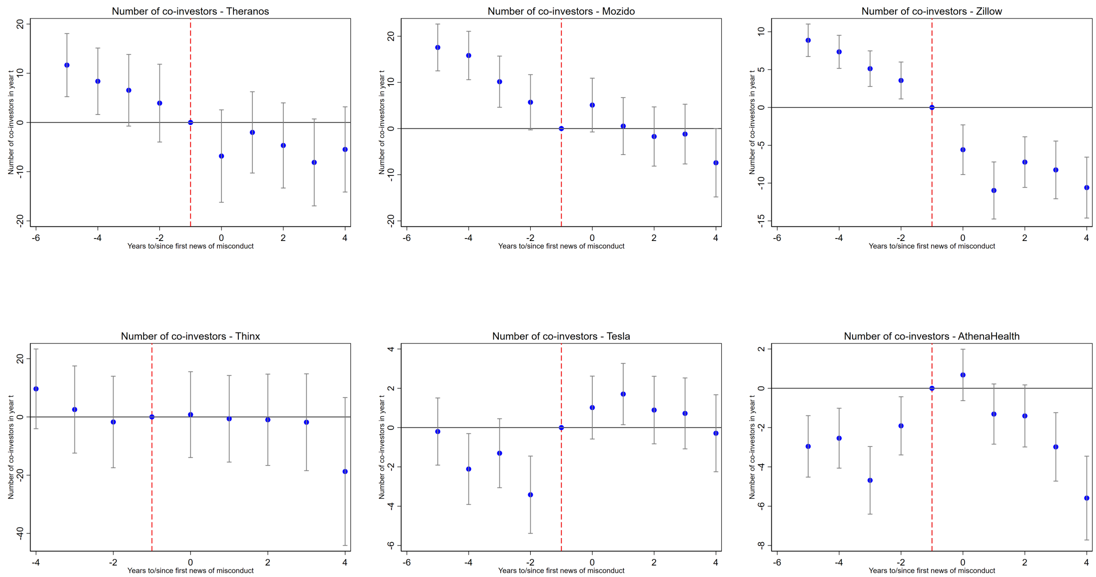

Figure 7: Effect of misconduct allegations on the number of co-investors in syndicated financing rounds by each case

Notes: This figure represents the event study estimating the effect of misconduct events on the number of co-investors in syndicated financing rounds between degree 0 and degree 1 investors relative to those between degree 1 and degree 2 investors for each of the six cases. We observed the syndicated financing round by degree 1 investors with degree 0 and degree 2 investors five years before a given misconduct event was reported for the first time in the news and ending five years after. The red dashed line marks the year before the misconduct allegation was reported for the first time in the news. It is the base period for estimating the difference-in-difference between the treatment and control group for the period after the misconduct allegation relative to the period before.

9 Appendix Tables

Table A1: Details of degree 0 and 1 investors by misconduct allegation event

Sno	Name of the alleged startup	Number of Degree 0 Investors	Number of Degree 1 Investors
1	Theranos	13	214
2	Mozido	5	434
3	Zillow	4	494
4	Thinx	1	128
5	Tesla	23	493
6	AthenaHealth	2	529
7	Total	48	2,292

This table provides details of the number of degree 0 and 1 investors for each of the misconduct allegation event in our sample.

Table A2: Placebo regression estimation with the amount invested per investor (in million US $) as the outcome variable

Ind. Variable	Overall	Technological misleading claims		Sexual Harassment		Non-Sexual Harassment	Financial
		Singulex	Corduro	SMTS	Cotopaxi	MEV	Aprima
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Placebo Treatment	-3.478***	-6.013***	-2.590***	-9.678***	-2.386***	-12.600***	-11.918***
	(0.084)	(0.217)	(0.118)	(1.553)	(0.122)	(2.515)	(0.867)
Dummy for Placebo Treatment* Dummy for Post Placebo Misconduct Allegation	**-1.657***** **(0.209)**	**-1.421**** **(0.562)**	**-1.414***** **(0.302)**	**3.234*** **(1.775)**	**-2.111***** **(0.322)**	**-1.433** **(4.472)**	**-0.618** **(1.172)**
Placebo Degree 1 Investors Syndication Activity	0.352*** (0.035)	0.366*** (0.058)	0.325*** (0.066)	1.043** (0.443)	0.343*** (0.053)	1.493** (0.708)	1.307*** (0.304)
Constant	3.472***	5.986***	2.562***	4.160***	3.039***	6.098*	5.838***
	(0.165)	(0.299)	(0.184)	(1.402)	(0.180)	(3.579)	(1.464)
Observations	121,140	24,560	40,160	1,180	52,500	460	2,280
R-square	0.202	0.174	0.212	0.321	0.202	0.389	0.471
Fixed Effects							
Misconduct Type	Yes	No	No	No	No	No	No
Placebo Degree 1 Investors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the placebo regression with the amount invested per investor (in million US $) as the outcome variable. Here, we replaced the degree 0 investors who had invested in alleged startups with placebo degree 0 investors. We did this by considering degree 0 investors who had invested in startups (innocent) similar to the alleged startups. We considered the establishment year and technology developed by startups to identify those that are similar to the alleged startup. Thus, we identified the following startups and correspondingly degree 0 investors: (a) Singulex similar to Theranos, (b) Corduro similar to Mozido, (c) Sell my timesshare (SMTS) similar to Zillow, (d) Cotopaxi similar to Thinx, (e) Miles Electric Vehicles (MEV) similar to Tesla, and (f) Aprima Medical Software similar to AthenaHealth. In addition to this, we changed the year of the misconduct allegation revelation to five years earlier than its original revelation in the news for the first time. Dummy for Placebo Treatment is an indicator variable that equals one for syndicated financing rounds between placebo degree 0 and 1 investors; and zero for syndicated financing rounds between placebo degree 1 and 2 investors. Placebo Degree 1 Investors Syndication Activity captures the level of syndication activity by placebo degree 1 investors in a particular year t. Robust standard errors are provided in parentheses and significance levels are noted as follows: * - $p < 0.10$; ** - $p < 0.05$, and *** - $p < 0.001$.

Table A3: Placebo regression results with the total amount invested (in million US $) as the outcome variable

Ind. Variable	Overall	Technological misleading claims		Sexual Harassment		Non-Sexual Harassment	Financial
		Singulex	Corduro	SMTS	Cotopaxi	MEV	Aprima
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Placebo Treatment	-12.867***	-22.794***	-9.459***	-35.117***	-8.227***	-57.168***	-52.337***
	(0.300)	(0.775)	(0.409)	(5.034)	(0.433)	(11.538)	(3.811)
Dummy for Placebo Treatment* Dummy for Post Placebo Misconduct Allegation	**-4.319*****	**-2.539**	**-3.527*****	**12.718****	**-6.481*****	**12.056**	**0.228**
	(0.794)	**(1.870)**	**(1.032)**	**(5.816)**	**(1.365)**	**(16.584)**	**(4.988)**
Placebo Degree 1 Investors Syndication Activity	1.495***	1.433***	1.335***	3.272**	1.535***	5.779*	6.027***
	(0.129)	(0.199)	(0.215)	(1.514)	(0.213)	(3.020)	(1.504)
Constant	13.192***	22.613***	9.484***	16.471***	11.644***	24.612	24.665***
	(0.567)	(0.975)	(0.599)	(5.201)	(0.694)	(15.259)	(7.131)
Observations	121,140	24,560	40,160	1,180	52,500	460	2,280
R-square	0.209	0.200	0.241	0.349	0.191	0.403	0.470
Fixed Effects							
Misconduct Type	Yes	No	No	No	No	No	No
Placebo Degree 1 Investors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the placebo regression with the total amount invested (in million US $) as the outcome variable. Here, we replaced the degree 0 investors who had invested in alleged startups with placebo degree 0 investors. We did this by considering degree 0 investors who had invested in startups (innocent) similar to the alleged startups. We considered the establishment year and technology developed by startups to identify those that are similar to the alleged startup. Thus, we identified the following startups and correspondingly degree 0 investors: (a) Singulex similar to Theranos, (b) Corduro similar to Mozido, (c) Sell my timesshare (SMTS) similar to Zillow, (d) Cotopaxi similar to Thinx, (e) Miles Electric Vehicles (MEV) similar to Tesla, and (f) Aprima Medical Software similar to AthenaHealth. In addition to this, we changed the year of the misconduct allegation revelation to five years earlier than its original revelation in the news for the first time. Dummy for Placebo Treatment is an indicator variable that equals one for syndicated financing rounds between placebo degree 0 and 1 investors; and zero for syndicated financing rounds between placebo degree 1 and 2 investors. Placebo Degree 1 Investors Syndication Activity captures the level of syndication activity by placebo degree 1 investors in a particular year t. Robust standard errors are provided in parentheses and significance levels are noted as follows: * - $p < 0.10$; ** - $p < 0.05$, and *** - $p < 0.001$.

Table A4: Placebo regression results with the number of co-investors as the outcome varaible

Ind. Variable	Overall	Technological misleading claims		Sexual Harassment		Non-Sexual Harassment	Financial
		Singulex	Corduro	SMTS	Cotopaxi	MEV	Aprima
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy for Placebo Treatment	-2.555***	-4.587***	-1.824***	-6.244***	-1.704***	-9.652***	-9.791***
	(0.047)	(0.118)	(0.074)	(0.497)	(0.065)	(1.543)	(0.642)
Dummy for Placebo Treatment* Dummy for Post Placebo Misconduct Allegation	**-1.407*****	**-1.354*****	**-1.248*****	**0.892**	**-1.627*****	**1.974**	**-1.553***
	(0.106)	**(0.217)**	**(0.192)**	**(0.642)**	**(0.158)**	**(2.089)**	**(0.910)**
Placebo Degree 1 Investors Syndication Activity	0.875***	0.761***	0.947***	0.647***	0.864***	1.006**	1.111***
	(0.048)	(0.119)	(0.088)	(0.137)	(0.067)	(0.404)	(0.264)
Constant	1.920***	3.052***	1.897***	3.376***	2.340***	4.175**	5.781***
	(0.159)	(0.441)	(0.267)	(0.538)	(0.215)	(1.867)	(1.290)
Observations	121,140	24,560	40,160	1,180	52,500	460	2,280
R-square	0.511	0.486	0.495	0.490	0.546	0.514	0.519
Fixed Effects							
Misconduct Type	Yes	No	No	No	No	No	No
Placebo Degree 1 Investors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the placebo regression with the number of co-investors in a syndicated financing round as the outcome variable. Here, we replaced the degree 0 investors who had invested in alleged startups with placebo degree 0 investors. We did this by considering degree 0 investors who had invested in startups (innocent) similar to the alleged startups. We considered the establishment year and technology developed by startups to identify those that are similar to the alleged startup. Thus, we identified the following startups and correspondingly degree 0 investors: (a) Singulex similar to Theranos, (b) Corduro similar to Mozido, (c) Sell my timesshare (SMTS) similar to Zillow, (d) Cotopaxi similar to Thinx, (e) Miles Electric Vehicles (MEV) similar to Tesla, and (f) Aprima Medical Software similar to AthenaHealth. In addition to this, we changed the year of the misconduct allegation revelation to five years earlier than its original revelation in the news for the first time. Dummy for Placebo Treatment is an indicator variable that equals one for syndicated financing rounds between placebo degree 0 and 1 investors; and zero for syndicated financing rounds between placebo degree 1 and 2 investors. Placebo Degree 1 Investors Syndication Activity captures the level of syndication activity by placebo degree 1 investors in a particular year t. Robust standard errors are provided in parentheses and significance levels are noted as follows: * - $p < 0.10$; ** - $p < 0.05$, and *** - $p < 0.001$.

Table A5: Details of technological misconduct allegations that satisfy the timing criterion

Sno	Startup name	Year of Misconduct	Title of the article	Investors' Network size	Extent of media coverage
(1)	(2)	(3)	(4)	(5)	(6)
1	**Theranos**	**2015**	**Mega-hot biotech startup Theranos calls WSJ takedown 'baseless'.**	**227**	**283**
2	**Mozido**	**2016**	**The Financial Industry's Theranos?**	**439**	**12**
3	Calico Energy	2014	City of Naperville files lawsuit against Calico Energy.	31	4
4	Coin	2016	Coin hit by class action suit claiming 'False Advertising'.	5909	1

Notes: This table presents the technological misleading claims that satisfy the timing criterion. The allegations have been arranged in descending order based on the extent of media coverage of misconduct allegations against the startup since its initial reporting up to 2021. Investors' network size is the sum of degree 0 and 1 investors' during the period before the misconduct allegation. Degree 0 investors are those who had directly invested with the alleged startup before the misconduct allegation was reported for the first time. Degree 1 investors are those who syndicated with Degree 0 investors investing in financing rounds raised by startups, except the alleged startups, during the period before the misconduct allegation was reported for the first time. The emboldened misconduct allegations are the ones that meet both timing and computation feasibility criteria; therefore, these events were considered for constructing the final sample.

Table A6: Details of sexual harassment allegations that satisfy the timing criterion

Sno	Startup name	Year of Misconduct	Title of the article	Investors Network size	Extent of media coverage
(1)	(2)	(3)	(4)	(5)	(6)
1	Sofi	2017	Another Silicon Valley startup faces sexual harassment claims.	2840	53
2	WeWork	2016	Labor disputes plague Bay Area company WeWork.	4685	27
3	**Zillow**	**2014**	**Zillow sued for sexual harassment.**	**498**	**12**
4	Github	2014	Former GitHub CEO is placed on leave.	1428	8
5	Square	2013	Sex Scandal Forces Square COO's Resignation.	2007	6
6	Betterworks	2017	BetterWorks CEO to step down following accusations of assault, sexual harassment.	5175	6
7	**Thinx**	**2017**	**Thinx "She-E-O" responds to allegations of toxic workplace.**	**129**	**4**
8	MagicLeap	2017	Magic Leap sued for sex discrimination & false marketing.	6889	3
9	Boundary	2016	Atlanta man labeled a groper by tabloid feels betrayed.	920	2
10	Sendgrid	2013	Hackers got a woman fired by a startup after she called out sexual harassment.	5997	10

Notes: This table presents the sexual harassment allegations that satisfy the timing criterion. The allegations have been arranged in descending order based on the extent of media coverage of misconduct allegations against the startup since its initial reporting up to 2021. Investors' network size is the sum of degree 0 and 1 investors' during the period before the misconduct allegation. Degree 0 investors are those who had directly invested with the alleged startup before the misconduct allegation was reported for the first time. Degree 1 investors are those who syndicated with Degree 0 investors investing in financing rounds raised by startups, except the alleged startups, during the period before the misconduct allegation was reported for the first time. The emboldened misconduct allegations are the ones that meet both timing and computation feasibility criteria; therefore, these events were considered for constructing the final sample.

Table A7: Details of non-sexual harassment allegations that satisfy the timing criterion

Sno	Startup name	Year of Misconduct	Title of the article	Investors Network size	Extent of media coverage
(1)	(2)	(3)	(4)	(5)	(6)
1	**Tesla**	**2009**	**AUTOS: Tesla co-founder sues company, CEO**	**493**	**509**
2	Palantir Technologies	2016	Palantir charged with hiring bias against Asians; Data analytics firm says it plans to fight discrimination suit.	2665	6

Notes: This table presents the non-sexual harassment allegations that satisfy the timing criterion. The allegations have been arranged in descending order based on the extent of media coverage of misconduct allegations against the startup since its initial reporting up to 2021. Investors' network size is the sum of degree 0 and 1 investors' during the period before the misconduct allegation. Degree 0 investors are those who had directly invested with the alleged startup before the misconduct allegation was reported for the first time. Degree 1 investors are those who syndicated with Degree 0 investors investing in financing rounds raised by startups, except the alleged startups, during the period before the misconduct allegation was reported for the first time. The emboldened misconduct allegations are the ones that meet both timing and computation feasibility criteria; therefore, these events were considered for constructing the final sample.

Table A8: Details of financial fraud allegations that satisfy the timing criterion

Sno	Startup name	Year of Misconduct	Title of the article	Investors Network size	Extent of media coverage
(1)	(2)	(3)	(4)	(5)	(6)
1	**AthenaHealth**	**2010**	**The Pomerantz firm charges athenahealth, Inc. with securities fraud.**	**529**	**21**
2	Ubiome	2019	UBiome CEOs Resign From Biotech Startup Amid FBI Investigation	9907	15
3	LendUp	2016	Banks have reason for optimism in Treasury auction manipulation suit; FDIC says more have expressed interest in forming de novos.	4216	4
4	MotionLoft	2014	Former CEO of technology startup charged in investment scheme.	432	3
5	Skully	2016	Bankruptcy imminent for failed Indiegogo startup Skully.	4756	6

Notes: This table presents the financial fraud allegations that satisfy the timing criterion. The allegations have been arranged in descending order based on the extent of media coverage of misconduct allegations against the startup since its initial reporting up to 2021. Investors' network size is the sum of degree 0 and 1 investors' during the period before the misconduct allegation. Degree 0 investors are those who had directly invested with the alleged startup before the misconduct allegation was reported for the first time. Degree 1 investors are those who syndicated with Degree 0 investors investing in financing rounds raised by startups, except the alleged startups, during the period before the misconduct allegation was reported for the first time. The emboldened misconduct allegations are the ones that meet both timing and computation feasibility criteria; therefore, these events were considered for constructing the final sample.

10 Appendix Figures

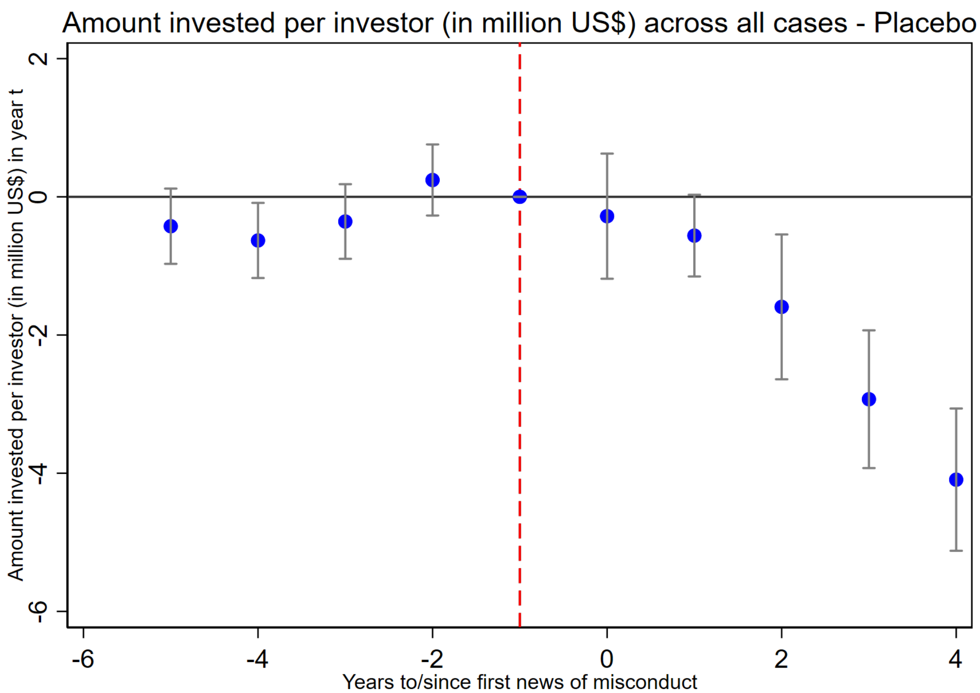

Figure A1: Placebo regression results with the amount invested per investor (in million US $) as the outcome variable

Notes: This figure represents the placebo event study estimating the effect on the amount invested per investor (in million US $) in syndicated financing rounds between placebo degree 0 and degree 1 investors relative to those between placebo degree 1 and degree 2 investors. Here, we replaced the degree 0 investors who had invested in alleged startups with placebo degree 0 investors. We did this by considering degree 0 investors who had invested in startups (innocent) similar to the alleged startups. We considered the establishment year and technology developed by startups to identify those that are similar to the alleged startup. Thus, we identified the following startups and correspondingly degree 0 investors: (a) Singulex similar to Theranos, (b) Corduro similar to Mozido, (c) Sell my timesshare (SMTS) similar to Zillow, (d) Cotopaxi similar to Thinx, (e) Miles Electric Vehicles (MEV) similar to Tesla, and (f) Aprima Medical Software similar to AthenaHealth. In addition to this, we changed the year of the misconduct allegation revelation to five years earlier than its original revelation in the news for the first time. The red dashed line marks the year before the placebo misconduct allegation. It is the base period for estimating the difference-in-difference between the placebo treatment and control group.

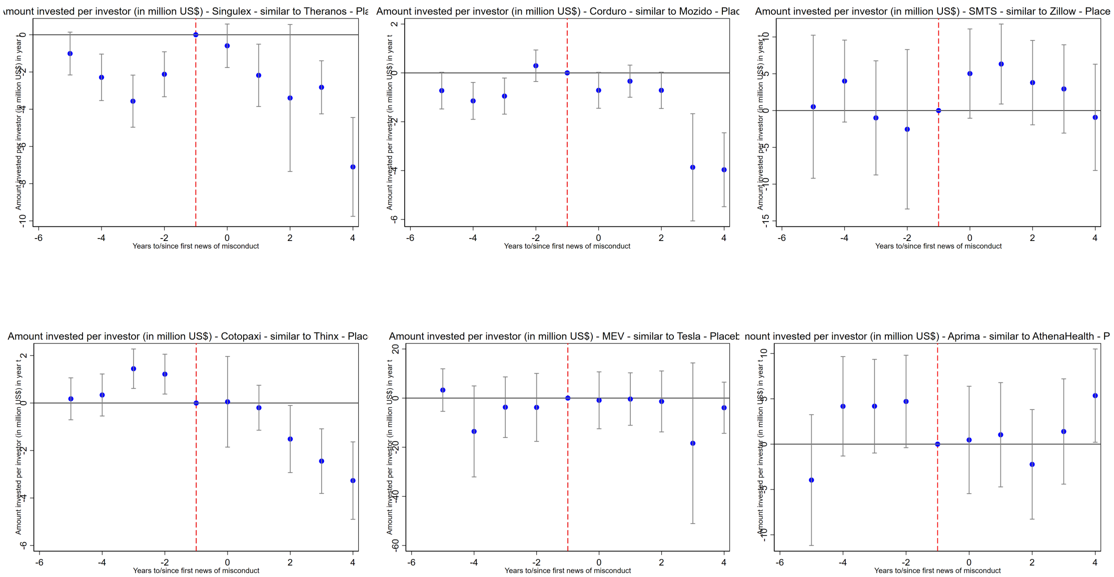

Figure A2: Placebo regression results with the amount invested per investor (in million US $) as the outcome variable by each case

Notes: This figure represents the placebo event study estimating the effect on the amount invested per investor (in million US $) in syndicated financing rounds between placebo degree 0 and degree 1 investors relative to those between placebo degree 1 and degree 2 investors for each case constituting our sample. Here, we replaced the degree 0 investors who had invested in alleged startups with placebo degree 0 investors. We did this by considering degree 0 investors who had invested in startups (innocent) similar to the alleged startups. We considered the establishment year and technology developed by startups to identify those that are similar to the alleged startup. Thus, we identified the following startups and correspondingly degree 0 investors: (a) Singulex similar to Theranos, (b) Corduro similar to Mozido, (c) Sell my timesshare (SMTS) similar to Zillow, (d) Cotopaxi similar to Thinx, (e) Miles Electric Vehicles (MEV) similar to Tesla, and (f) Aprima Medical Software similar to AthenaHealth. In addition to this, we changed the year of the misconduct allegation revelation to five years earlier than its original revelation in the news for the first time. The red dashed line marks the year before the placebo misconduct allegation. It is the base period for estimating the difference-in-difference between the placebo treatment and control group.

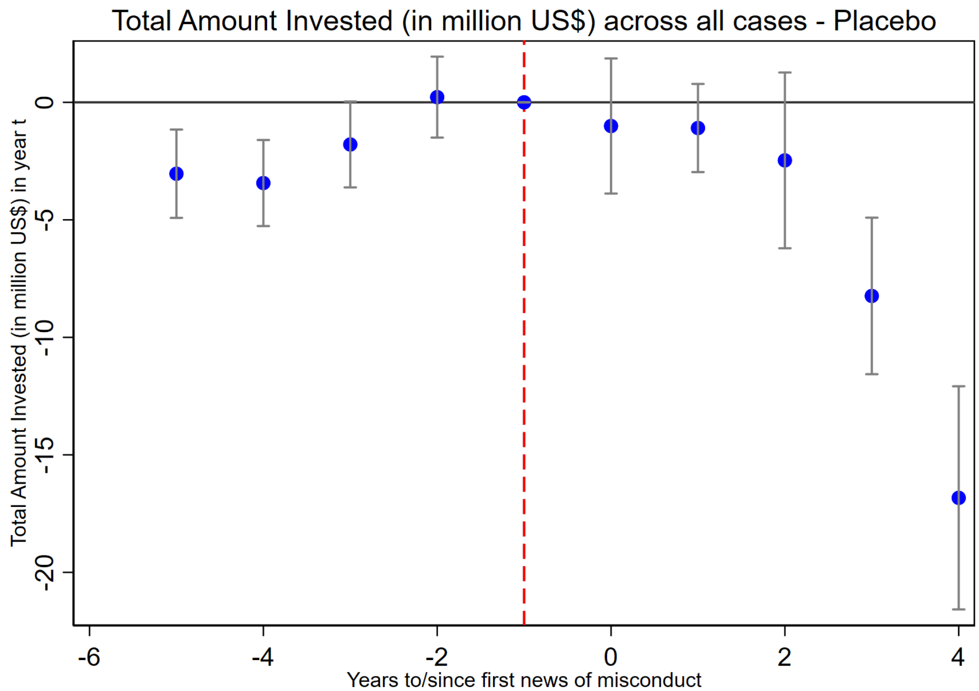

Figure A3: Placebo regression results with the total amount invested (in million US $) as the outcome variable

Notes: This figure represents the placebo event study estimating the effect on the total amount invested (in million US $) in syndicated financing rounds between placebo degree 0 and degree 1 investors relative to those between placebo degree 1 and degree 2 investors. Here, we replaced the degree 0 investors who had invested in alleged startups with placebo degree 0 investors. We did this by considering degree 0 investors who had invested in startups (innocent) similar to the alleged startups. We considered the establishment year and technology developed by startups to identify those that are similar to the alleged startup. Thus, we identified the following startups and correspondingly degree 0 investors: (a) Singulex similar to Theranos, (b) Corduro similar to Mozido, (c) Sell my timesshare (SMTS) similar to Zillow, (d) Cotopaxi similar to Thinx, (e) Miles Electric Vehicles (MEV) similar to Tesla, and (f) Aprima Medical Software similar to AthenaHealth. In addition to this, we changed the year of the misconduct allegation revelation to five years earlier than its original revelation in the news for the first time. The red dashed line marks the year before the placebo misconduct allegation. It is the base period for estimating the difference-in-difference between the placebo treatment and control group.

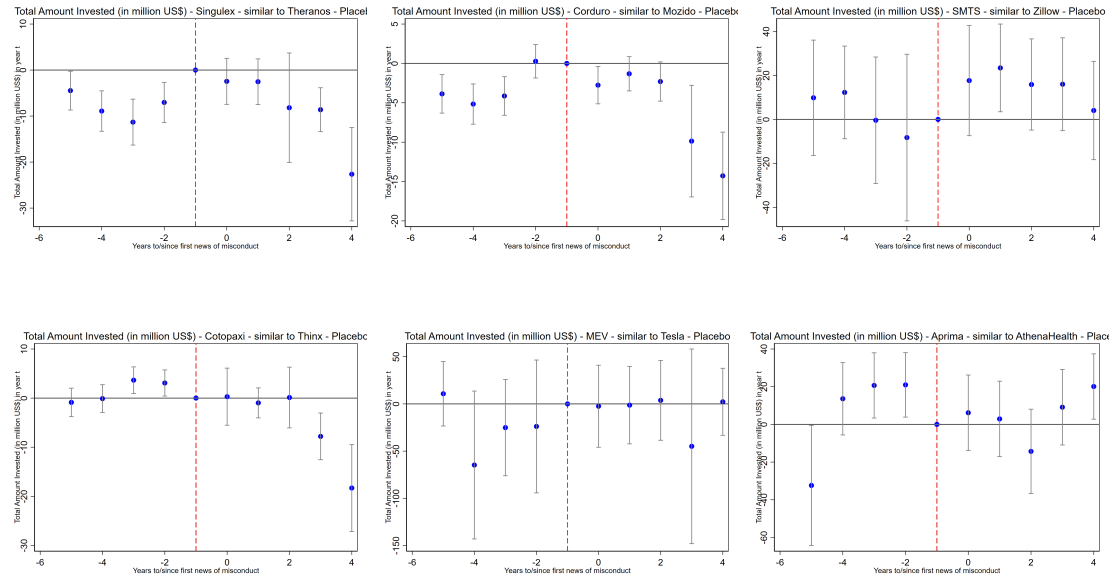

Figure A4: Placebo regression results with the total amount invested (in million US $) as the outcome variable by each case

Notes: This figure represents the placebo event study estimating the effect on the total amount invested (in million US $) in syndicated financing rounds between placebo degree 0 and degree 1 investors relative to those between placebo degree 1 and degree 2 investors. Here, we replaced the degree 0 investors who had invested in alleged startups with placebo degree 0 investors. We did this by considering degree 0 investors who had invested in startups (innocent) similar to the alleged startups. We considered the establishment year and technology developed by startups to identify those that are similar to the alleged startup. Thus, we identified the following startups and correspondingly degree 0 investors: (a) Singulex similar to Theranos, (b) Corduro similar to Mozido, (c) Sell my timesshare (SMTS) similar to Zillow, (d) Cotopaxi similar to Thinx, (e) Miles Electric Vehicles (MEV) similar to Tesla, and (f) Aprima Medical Software similar to AthenaHealth. In addition to this, we changed the year of the misconduct allegation revelation to five years earlier than its original revelation in the news for the first time. The red dashed line marks the year before the placebo misconduct allegation. It is the base period for estimating the difference-in-difference between the placebo treatment and control group.

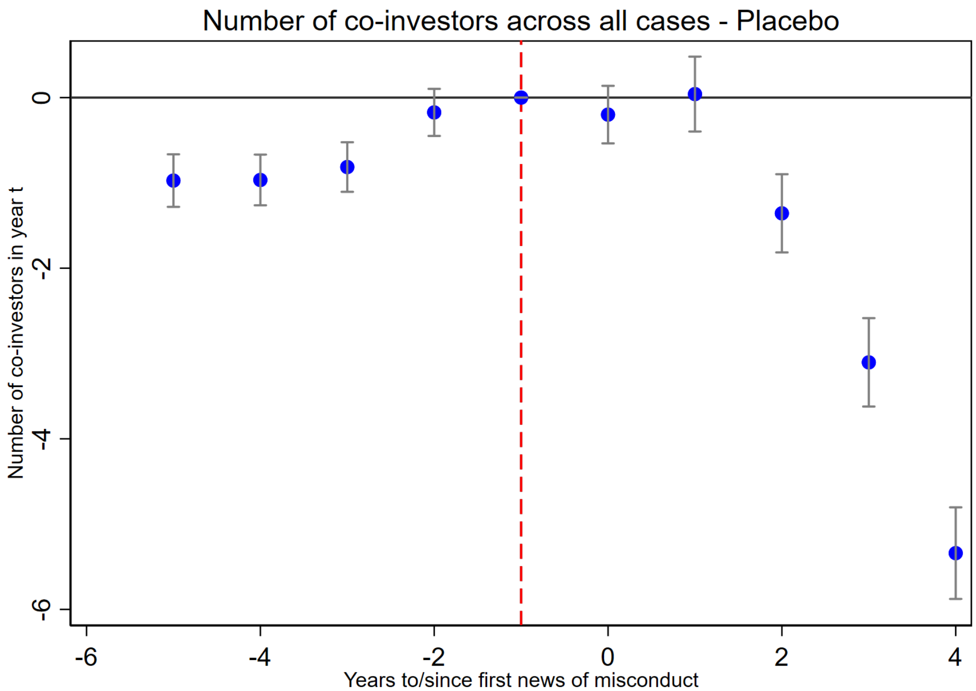

Figure A5: Placebo regression results with the number of co-investors as the outcome variable

Notes: This figure represents the placebo event study estimating the effect on the number of co-investors in syndicated financing rounds between placebo degree 0 and degree 1 investors relative to those between placebo degree 1 and degree 2 investors. Here, we replaced the degree 0 investors who had invested in alleged startups with placebo degree 0 investors. We did this by considering degree 0 investors who had invested in startups (innocent) similar to the alleged startups. We considered the establishment year and technology developed by startups to identify those that are similar to the alleged startup. Thus, we identified the following startups and correspondingly degree 0 investors: (a) Singulex similar to Theranos, (b) Corduro similar to Mozido, (c) Sell my timesshare (SMTS) similar to Zillow, (d) Cotopaxi similar to Thinx, (e) Miles Electric Vehicles (MEV) similar to Tesla, and (f) Aprima Medical Software similar to AthenaHealth. In addition to this, we changed the year of the misconduct allegation revelation to five years earlier than its original revelation in the news for the first time. The red dashed line marks the year before the placebo misconduct allegation. It is the base period for estimating the difference-in-difference between the placebo treatment and control group.

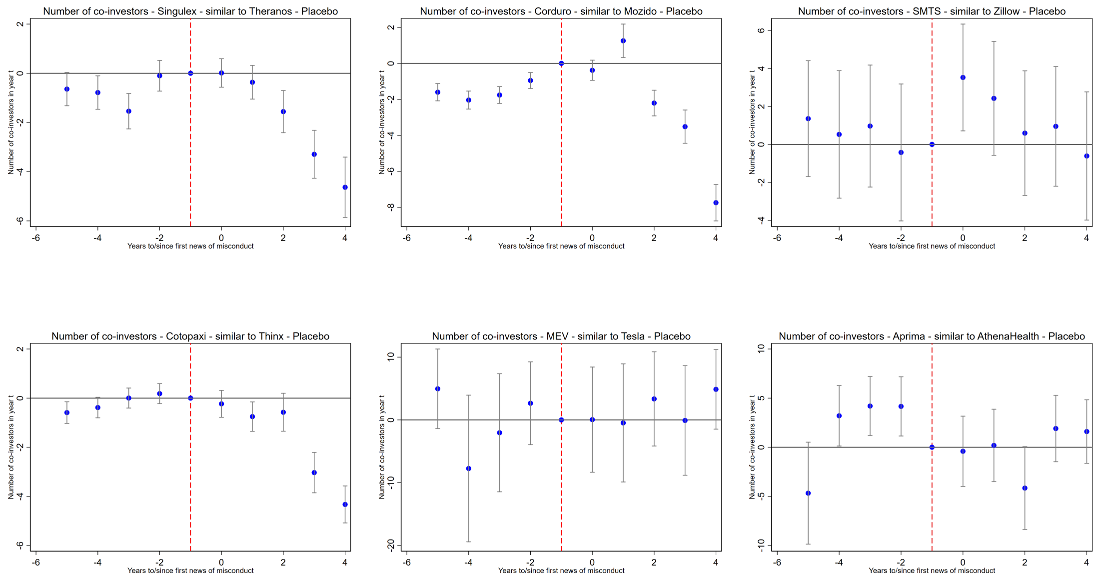

Figure A6: Placebo regression results with the number of co-investors as the outcome variable by each case

Notes: This figure represents the placebo event study estimating the effect on the number of co-investors in syndicated financing rounds between placebo degree 0 and degree 1 investors relative to those between placebo degree 1 and degree 2 investors. Here, we replaced the degree 0 investors who had invested in alleged startups with placebo degree 0 investors. We did this by considering degree 0 investors who had invested in startups (innocent) similar to the alleged startups. We considered the establishment year and technology developed by startups to identify those that are similar to the alleged startup. Thus, we identified the following startups and correspondingly degree 0 investors: (a) Singulex similar to Theranos, (b) Corduro similar to Mozido, (c) Sell my timesshare (SMTS) similar to Zillow, (d) Cotopaxi similar to Thinx, (e) Miles Electric Vehicles (MEV) similar to Tesla, and (f) Aprima Medical Software similar to AthenaHealth. In addition to this, we changed the year of the misconduct allegation revelation to five years earlier than its original revelation in the news for the first time. The red dashed line marks the year before the placebo misconduct allegation. It is the base period for estimating the difference-in-difference between the placebo treatment and control group.