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

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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.

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`Once famous for a supposedly innovative approach to blood testing, now infamous for allegedly faking it, the names Theranos and Elizabeth Holmes aren't fading away anytime soon. All of this has had a ripple effect for other companies that, like Theranos, were trying to make blood drawing and diagnostics easier for consumers'

- *Aaron Mak, Slate, September 7, 2021*

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 (Lerner & Kortum 2000, Gompers et al 2008, Howell 2017, Ewens et al 2018, Ewens & Farre-Mensa 2020). 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 et al 2019, Howell et al 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, it 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.[2] This has destroyed confidence[3] 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*".[4] It has also unleashed public ire over the role of politicians and regulators in governing the new financial technology.[5] 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.[6]

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

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[2] https://www.reuters.com/technology/ftxs-founder-dismisses-balance-sheet-concerns-false-rumors-2022-11-07/ [Accessed as on October 10th, 2023]
[3] https://www.forbes.com/sites/lawrencewintermeyer/2022/12/03/polyamory-denial-and-recriminations-rebuilding-trust-in-crypto-after-ftx/ [Accessed as on October 10th, 2023]
[4] https://www.reuters.com/technology/crypto-market-still-bears-scars-ftxs-collapse-2023-10-03/#:~:text=CRUMBLING%20MARKET%20CAP,trillion%20most%20of%20this%20year. [Accessed as on October 10th, 2023]
[5] https://www.politico.com/news/magazine/2022/12/09/crypto-scandal-sam-bankman-fried-ftx-00073178 [Accessed as on October 10th, 2023]
[6] https://www.bloomberg.com/opinion/articles/2018-06-18/theranos-didn-t-just-harm-investors [Accessed as on October 10th, 2023]

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 misconduct 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 events that an entire technological area or entrepreneurial cluster may be "tainted" and prone to similar offences. 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.[7] 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.[8]

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 make use of 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 allow us to estimate the causal effects of misconduct allegations adopting a stacked difference-in-difference model that evaluate the change in performances of treatment and control group 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 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

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

[8] 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]

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.

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 et al (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 et al 2015). This literature has focused on the characteristics of firms involved in frauds (Burns & Kedia 2006, Efendi et al 2007), factors predicting fraud (Dimmock & Gerken 2012, Parsons et al 2018) and the mechanisms for detecting it (Dyck et al 2010), effects of corporate frauds on household stock market participation and investment advisers (Giannetti & Wang 2016, Gurun et al 2018), and penalties paid by managers responsible for corporate misconduct and by outside directors of sued firms (Karpoff et al 2008, Fich & Shivdasani 2007). 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 (Lerner 2000, Hellmann & Puri 2002, Sorensen 2007, Bottazzi et al 2008, Bernstein et al 2016), but attracting this form of capital is hampered by information frictions inherent in investor-startup relationship (Gompers 1995, Hsu 2004, Conti et al 2013, Bottazzi et al 2016, Howell 2020). 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 (Townsend 2015, Conti et al 2019). 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 et al 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 (Paruchuri & Misangyi 2015, Naumovksa & Zajac 2022) 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 et al 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 (Gompers 1995, Bergemann et al 2008, 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. 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 et al 2012), passion (Chen et al 2009), entrepreneur's willingness to learn and adapt (Ciuchta et al 2018), network with prominent investors (Hsu & Ziedonis 2013), and others, relative to objective judgements based on market-related factors (Kirsch et al 2009, Huang & Pearce 2015).

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 (Yue et al 2013, Paruchuri & Misangyi 2015, Bruyaka et al 2018, Baker et al 2019, Yin et al 2021). 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 they tend to suspect similar illegitimate practices to be abound in innocent startups (Jonsson et al 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 (Hsu 2004, Nahata 2008, Chahine et al 2021).

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 termination of an under-performing ventures or those who 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]

Zuckerman (2000, 2012), and Paruchuri & Misangyi (2015) 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.

Naumovksa & 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.

[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.

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.

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,

[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]

[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) and 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.

including misconduct cases involving Theranos, WeWork, Uber, and FTX[13,14,15,16], 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 Naumovksa & 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 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

[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/ [Accessed on June 28th, 2023]
[14]https://www.wired.com/story/theranos-and-silicon-valleys-fake-it-till-you-make-it-culture/ [Accessed on June 28th, 2023]
[15]https://www.theguardian.com/technology/2022/jan/04/elizabeth-holmes-verdict-analysis [Accessed on June 28th, 2023]
[16]https://stanfordreview.org/lets-put-the-brakes-on-fake-it-till-you-make-it/ [Accessed on June 28th, 2023]

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 et al 2007, Julio & Hook 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 Online 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 and Roche (2021), 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:

1. *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.[17]
2. *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.[18]
3. *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.[19]
4. *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

[17]"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].
[18]"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].
[19]"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].

Theranos, where its founders misled everyone about their blood-testing technology as exposed by a Wall Street Journal article published in 2015.[20]

5. *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 Table A1 to A5 of the Online Appendix.

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 Cengiz et al (2019), Baker et al (2022), and Bleiberg (2021) 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

[20]"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].

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[21]. 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.[22] 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), (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

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

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

the control group relative to the treatment group. We opted for a balanced sample and therefore randomly assigned one control startup – among those eligible[23] - 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. 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. Econometric Model

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

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

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 Eq. (1) given below:

$$Y_{ijkst} = \propto + \beta_1 Post\ Misconduct_{jt} + \beta_2 Post\ Misconduct_{jt} * Tech.Similar\ Startup_{ij} + \gamma Ln.Age_{it} + \omega_i + \varphi_j + \theta_{kt} + \tau_{st} + \varepsilon_{ijtks} \text{ ----- Eq (1)}$$

Y_{ijkst} 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 $Tech.Similar\ Startup_{ij}$ 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 $Post\ Misconduct_{jt}$ 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.[24] 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 Eq. (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 *i's* age in Eq. (1) to control *i's* position in its life cycle. The φ_j represents the fixed effect for misconduct allegation *j*. Moreover, we introduce θ_{kt} to control for any sector-specific time-varying unobservable heterogeneities. τ_{st} is a state-by-year fixed effect controlling for any time-varying geographical trends, while ε_{ijtks} 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

[24]Note that the five-year period before and after the misconduct allegation is reported for the first time constitutes the period of analysis for all the regression estimates provided here. For the event studies, we make use of the period constituting five-year before the misconduct allegation is reported for the first time in the news and ten-years after the misconduct allegation was reported. This approach facilitates in providing a glimpse into the persistence of the impact of misconduct allegations.

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 $Post\ Misconduct_{jt} * Tech.Similar\ Startup_{ij}$, 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, $Post\ Misconduct_{jt} * Tech.Similar\ Startup_{ij}$, 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, $Post\ Misconduct_{jt} * Tech.Similar\ Startup_{ij}$, 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 $Tech-$

$State\ Similar\ Startup_{ij}$. 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 $Post\ Misconduct_{jt} * Tech.Similar\ Startup_{ij} * MisconductType_{i}$ 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.[25]

[25]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.

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 beyond Series B before the misconduct allegations were reported. We introduce a tripe-interaction of $Post\ Misconduct_{jt} * Tech.Similar\ Startup_{ij} * \ ExAnteStage_j$ 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[26]. 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.[27] 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 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

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

[27]We make use of the formula $C_{mkt} = \frac{(N_{mkt}*100)}{TN_{mt}}$ where N_{mkt} 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_{mt} 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 $C_{mkt} \geq 50$ % ; and non-core sector otherwise.

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.[28] The regression results for likelihood of participating in a round and log of amount raised based on this alternative definition is provided in Online Appendix Table 6 and 7 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.

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]

Column (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 - $Post\ Misconduct_{jt} * Tech.Similar\ Startup_{ij}$ 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 reduction in likelihood of exit opportunities. A potential rationale could be the duration between misconduct allegation 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:

[28]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 $C_{mkt} = \frac{(A_{mkt}*100)}{TA_{mt}}$ where A_{mkt} 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_{mt} 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 $C_{mkt} \geq 50$ % ; and non-core sector otherwise.

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 (Towsend 2015, Conti et al 2019). 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 2005, 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 (Shane & Cable 2002, Colombo 2021). In the case of financial misconduct, Pachuri & 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 (Hsu 2005, Agarwal et al 2015, Hallen & Pahnke 2016, 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 (Gompers 1995, Colombo 2021). 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 & Tumlison 2014, Tzabbar & Margolis 2017, Ko & Mckelvie 2018). 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 et al 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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Tables

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

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: $Post\ Misconduct_{jt} * Tech.Similar\ Startup_{ij} * \ MisconductType_i$. 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***** **[0.0065]**	**-0.0041** **[0.0211]**
R2	0.3096	
Observations	288,317	
	Panel (B): Ln. Amount Raised	
	(1)	(2)
Tech. similar startup X Post misconduct	**-0.2768***** **[0.0910]**	**-0.1981** **[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: $Post\ Misconduct_{jt} * Tech.Similar\ Startup_{ij} * \ ExAnteStage_j$. 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

	Prob. Of Obt. A Round – VC	Ln. Amt Raised – VC	Prob. Of Obt. A Round – Prom. VCs	Ln. Amt Raised – Prom. VCs	Prob. Of Obt. A Round – Non VC	Ln. Amt Raised – Non VC
	(1)	(2)	(3)	(4)	(5)	(6)
Post misconduct	0.0017	0.0235	0.0023*	0.0321*	0.0079**	0.1079**
	[0.0017]	[0.0260]	[0.0012]	[0.0190]	[0.0033]	[0.0457]
Tech. similar startups X Post misconduct	**-0.0104*** **	**-0.1553*** **	**-0.0081*** **	**-0.1217*** **	**-0.0162*** **	**-0.2169*** **
	[0.0028]	**[0.0433]**	**[0.0022]**	**[0.0334]**	**[0.0049]**	**[0.0690]**
Ln. Startup age	0.0166***	0.2938***	0.0081***	0.1491***	-0.0087*	-0.0292
	[0.0024]	[0.0397]	[0.0019]	[0.0327]	[0.0048]	[0.0643]
Constant	-0.0040	-0.1196*	-0.0006	-0.0440	0.0556***	0.6287***
	[0.0040]	[0.0658]	[0.0032]	[0.0536]	[0.0089]	[0.1206]
R2	0.253	0.259	0.231	0.236	0.234	0.233
Observations	288,317	288,317	288,317	288,317	288,317	288,317
Misconduct FE	Y	Y	Y	Y	Y	Y
Startup FE	Y	Y	Y	Y	Y	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 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.

Figures

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

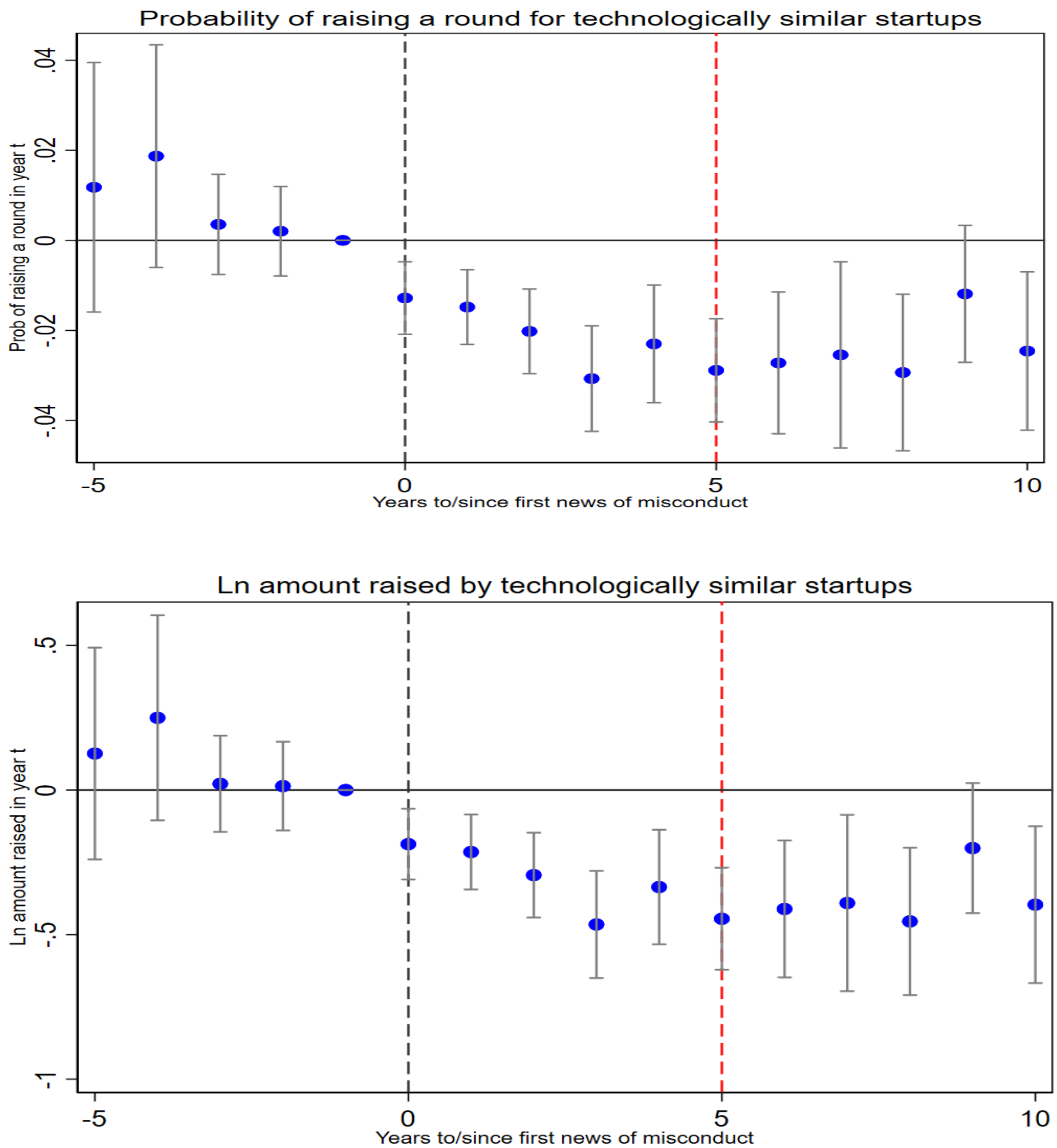


Figure 1: Effects of misconduct allegations on technologically similar startups

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.

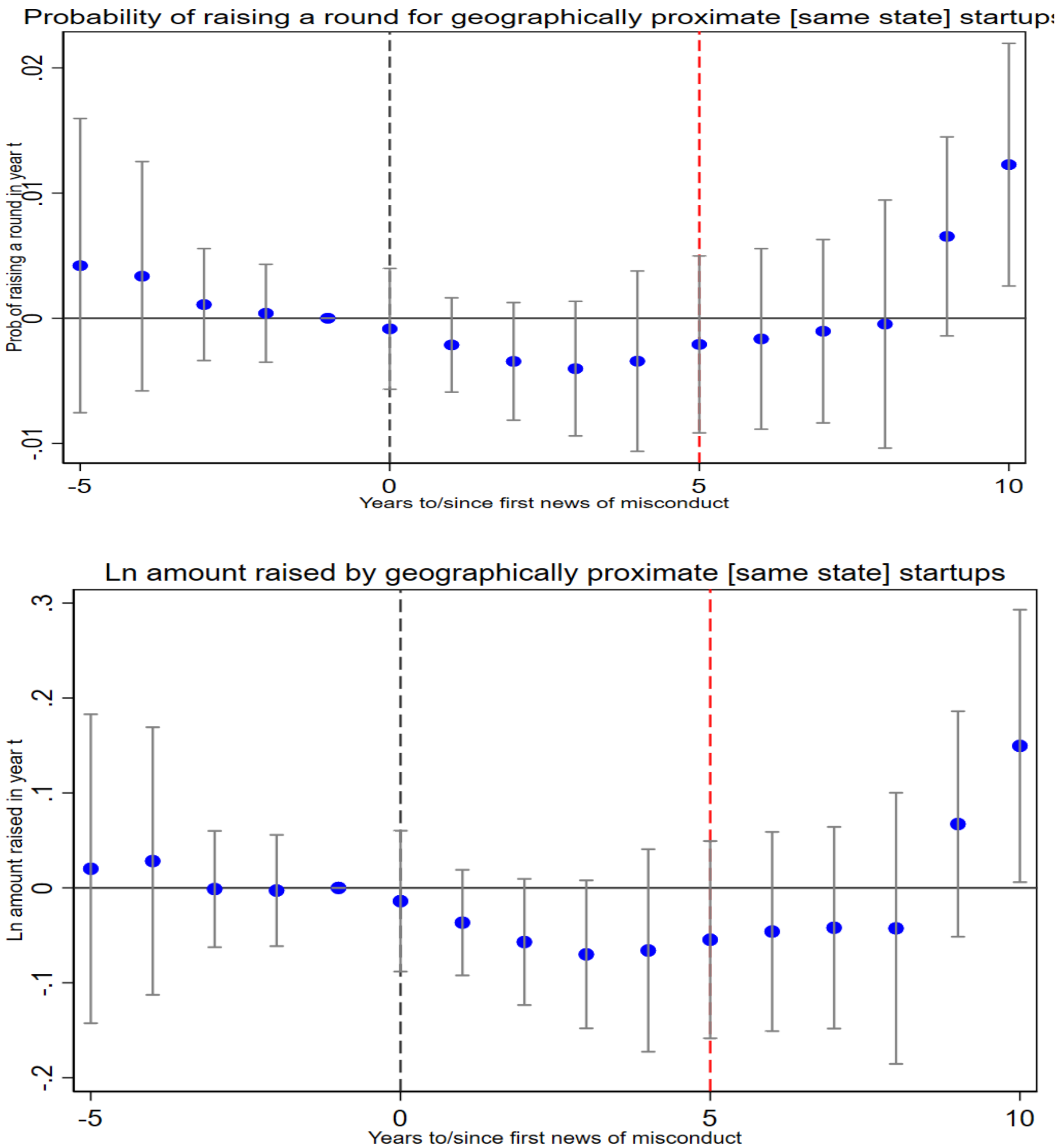


Figure 2: Effects of misconduct allegations on geographically proximate startups

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.

Online Appendix Tables

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

Online Appendix Table 1: 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.

Online Appendix Table 2: 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.

Online Appendix Table 3: 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).

Online Appendix Table 4: 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.

Online Appendix Table 5: 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.

Online Appendix Table 6: 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.

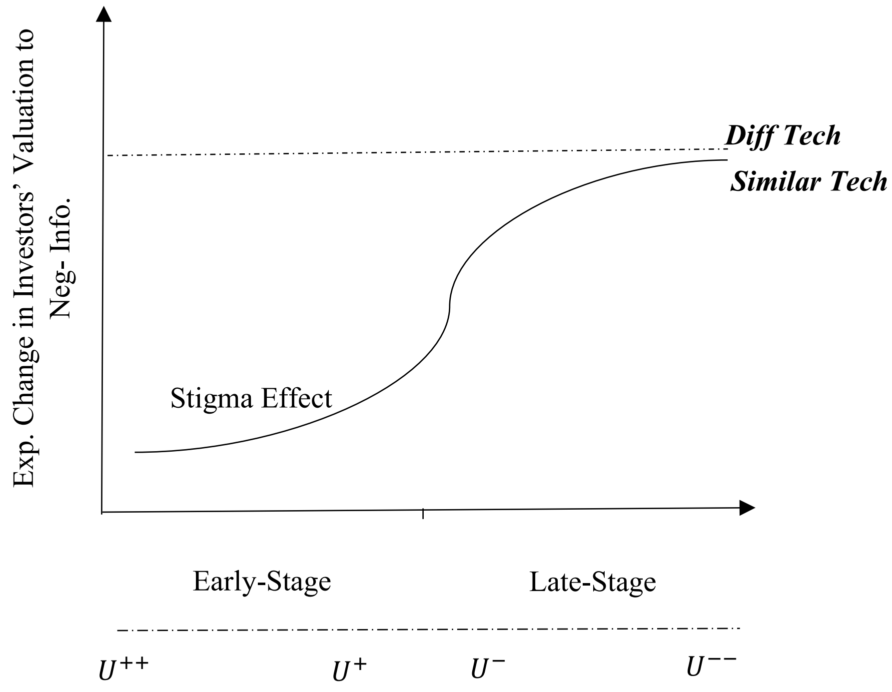
Online Appendix Table 7: Unpacking the investment choices of investors by alternative definition of Core and Non-Core Sectors – Log of Amount Raised

	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.

Online Appendix Figures

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



Online Appendix Figure 1: 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.