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Improving Investor-Investee Matches with Regulation: Evidence from the Orphan Drug Act & Global Biotechnology Industry

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Abstract

Venture capitalists (VCs) ideally like to invest in innovations at a nascent stage but this is inherently incorporated with huge risks (Ruhnka and Young 1991, Gompers 1995). Because it is difficult to value novel technologies at an early development stage, VCs may be herding into financing advanced-stage projects for which an archive of scientific knowledge and commercial performance are available that enables a correct valuation (Lerner 2009). A response to this market failure in investor-investee matches might be an institutional change that can steer investors towards supporting new innovations at an early stage, providing more information necessary to value young projects. Using the setting of the Orphan Drug Act (ODA) in the European Union (EU) enacted in 1999, we test these ideas in the fields of biotechnology using a difference in difference methodology and find that VCs are indeed more likely to invest in early-stage technologies in sub-fields disproportionately affected by ODA. In addition, we document that exit performances of VC-backed startups do not get worse as a result of VCs investing into early-stage innovations. Our results suggest that VCs are enabled to make fully-informed decisions as ODA provides some additional information on early-stage technologies. We conclude discussing the role of public policy in correcting market failure between investor-investee matches in the market for entrepreneurial finance.

KEY WORDS: venture capital; entrepreneurial finance; innovation; valuation problem; early-stage ventures; biotechnology & pharmaceuticals

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1 Introduction

Venture Capital firms (VCs) are important engines for delivering breakthrough innovations to market (Tyebjee and Bruno 1984, Bygrave and Timmons 1992, Kortum and Lerner 2000). Radical innovations that affect the entire trajectory of an industry and social welfare mostly come from risk-taking efforts, but large established firms may lack organizational capabilities to identify and benefit from new opportunities (Christensen 1993). Startup ventures have increasingly occupied this niche of new opportunities over the last few decades thereby pushing the scientific frontier (Shan, Walker et al. 1994, Pisano 2006, Hughes 2011). Yet, entrepreneurial innovators can hardly deliver disruptive innovations all the way to markets without securing sustained flow of financial capital (Paik and Woo 2014). VCs play a considerable role in investing in early stage technologies of startups, serving as financial intermediaries so that startup innovators can advance technologies enough to partner with established firms with commercialization capabilities (Ferrary and Granovetter 2009).

However, questions linger as to what extent VCs finance innovations pushing the scientific frontier (Branscomb and Auerswald 2002, Dimov and Murray 2007, Parhankangas 2007). Despite the considerably crucial roles of VCs in nurturing up-to-date innovations, there have been growing concerns on the risk-averse investment by VCs. Some practitioners and policy makers comment that VC firms tend to invest contemporaneously in very similar technologies, evidenced by the "herding behaviors" of VCs in the biotechnology universe, rather than identifying exploratory businesses that are expected to solve important challenges (Branscomb and Auerswald 2002, Dimov and Murray 2007). In addition there is now evidence that since 1990s, the portfolio of VCs has switched from early-stage investments to late-stage counterparts (Lerner 2009). Founders Fund, one of the co-investors of Facebook, claims in its mission statement that in the late 1990s, venture investing shifted away from funding transformational firms to firms that solved incremental problems or even fake problems, which made sense only for a brief period backed by an enormous stock market bubble (Gibney 2011). An anticipated outcome herein is the underfinancing of novel innovations that may remarkably impact economic prosperity in the long run.

Given this potential market failure in investor-investee matches in early stage transformational ventures over time, environmental & organizational factors affecting the investment decisions of VCs have received renewed attention (Landström 2007). Nanda and Rhodes-Kropf (2013) find that VCs are more likely to invest in risky startups in a 'hot' market (Nanda and Rhodes-Kropf 2013). Lerner (2002) reports the cyclical nature of venture funding, noting that government policies could substantially improve the environment for venture capital investment by addressing gaps in the private funding process (Lerner 2002). Meanwhile, scholars also report that VCs view the quality of the management team as more important than the business model or market and discover deals primarily through their networks (MacMillan, Siegel et al. 1986, Gompers, Gornall et al. 2016). Among recent studies, Wu (2015) suggests that the collective decision making structure of VCs, along with the cost of acquiring tacit information about risky ventures, leads VCs to invest in less risky businesses relative to individual investors (Wu 2015).

Despite the repeated concerns on the herding mentality of VCs towards safer investments, we still have little evidence on the conditions that lead VCs to take risks to finance radical innovations at a premature stage. Does an institutional change affect to what extent VCs invest in nascent technologies and, if so, through what mechanisms? What are the implications of the changes in the risk profile of VCs' investment portfolio on their strategies and performances? This study aims to answer these questions by looking at the timing and the characteristics of VC investments in biotechnological innovations in the United States (US) and the European Union (EU) led by a change in the policy regime. The biotechnology industry is an ideal setting for this study as entrepreneurial firms and VCs are the leading source of technological advancement in this field (Moeen 2013, Chatterji and Fabrizio 2014, Howell 2015)

Using the setting of the Orphan Drug Act (ODA) enacted by EU, originally designed to facilitate the development of rare disease drugs, we study how the additional information provided by the regulatory shift helps VCs value the prospect of novel drug candidates at an earlier stage, thereby affecting the timing and the attributes of investments made by VCs. For example, the certification of orphan designation by regulatory agencies serves as a strong quality signal to investors and transfers tacit information into observable information, reducing information friction between a startup and an investor such as a VC

fund. It also facilitates information aggregation among partners within a VC, allowing the investing firm to finance novel innovations at an earlier stage.

Our empirical approach employs a difference-in-difference methodology. We compare investments by VCs that take place in technology areas disproportionately affected by ODA with those in less affected areas, within the boundary of broader bio-pharmaceutical fields. We find that VCs investing in areas significantly affected by ODA finance startups approximately 1 year younger than VCs investing in less affected areas. They are also 2% more likely to finance early-stage innovations from regions that have been previously underserved by VCs. Also, the investing firms are more likely to syndicate deals, arguably to diversify the higher level of uncertainty associated with funding young and risky ventures. Lastly, we observe that the investment performances of VCs do not get worse as a result of investing more in early-stage innovations. It implies that VCs make fully-informed decisions benefitting from the additional information provided by ODA. This is in contrast to simply speculating in more risky innovations.

By adding empirical evidence of the impact of valuation problem on the nature of investments backed by VCs, this study joins the lively discussion on the determinant of investment decisions by VCs (Birley 1986, Gompers, Gornall et al. 2016, Park and Tzabbar 2016) in extant literature. Early stage ventures are inherently endowed with higher level of risk and information asymmetry, leaving VCs vulnerable to market failure through adverse selection and/or moral hazard problems. We also document how VCs vary the level of syndication over different stages as ODA diminishes the burden of valuing nascent ventures.

In addition, this project makes broader contribution to the literature on the role of regulatory intervention to innovation. Innovations at the edge of scientific frontier often require long commitment to verify technological and commercial feasibility and incorporate high failure rates, which does not justify the investment from private sectors. Prior work therefore, has focused on the role of institutions in the entry and the growth of innovation (Dosi, Freeman et al. 1988, Branstetter, Chatterjee et al. 2011, Budish, Roin et al. 2013, Budish, Roin et al. 2015). The results of this paper show that the availability of a small market test led by a policy shift diminishes the market inefficiency in the market for

entrepreneurial financing, promoting VCs to explore on nascent ideas and thereby generating aggregate innovation in the industry.

We proceed as follows. Section 2 introduces a theoretical framework and discusses some testable hypotheses. Section 3 describes the empirical context and Section 4 discusses data. Section 5 explains our identification strategy and regression results from our econometric analysis follow in Section 6. Section 7 concludes.

2 Theory and Hypotheses

2.1. Technology Valuation and Underfinancing of Novel Innovations at Early-stage

Entrepreneurial firms have been seen as providers of revolutionary products that improve economic and social welfare (Schumpeter 1942, Birley 1986). However, developing a disruptive and exploratory innovation often requires a substantial amount of capital and long time commitment. Most startups lack financing resources to deliver an innovation at a nascent stage all the way to market. It is at this stage of development, however, that the conventional means of financing methods, including collateral-based funding from bank, are not available (Myers and Majluf 1984, Murray 1999). VCs have filled the financing gap to provide capitals for a significant period of time to potentially promising entrepreneurs operating on the frontier of new technologies and markets (Tyebjee and Bruno 1984; Bygrave and Timmons 1992).

Despite the conceived role of VCs as important financial intermediaries for novel products, the management of early-stage investment is challenging. Early stage investors are forced to face multiple sources of uncertainty spanning the commercial, technical and managerial aspects of new enterprises (Storey and Tether 1998). Management teams of many startups have little or no previous experiences in business. Novel innovations at an early stage often disrupt existing markets or even target non-existing markets. By definition, a genuinely revolutionary innovation lacks precedent evidence such as existing scientific knowledge or previous market performances of similar innovations, necessary to valuate the commercial and technological feasibility (Chan, Siegel et al. 1990, Amit, Brander et al. 1998). Thus, investors find it difficult to objectively value the prospect of the novel technologies or business models, often having them depend on their "gut feels"

to invest in such opportunities rather than deciding through verifiable valuation (Huang and Knight 2015, Huang and Pearce 2015).

Even worse, the tacit nature of information makes early-stage investors more vulnerable to information asymmetry problems such as adverse selection and moral hazard (Sahlman 1990, Storey and Tether 1998, Kerr, Nanda et al. 2014, Wu 2015). As a result, VCs have responded to the valuation challenge by switching from financing early-stage ventures to late-stage counterparts, raising concerns on the underfinancing of early-stage innovations (Alvarez-Garrido 2015).

Lastly, the typical governance structure of VCs may also exacerbate the reluctance against financing highly risky innovations. As a partnership, a typical VC consists of general partners who manage and invest the funds raised from limited partners. Most funds have a fixed duration from 5 to 8 year lifespan before the money is returned to the limited partners (Tyebjee and Bruno 1984, Bygrave and Timmons 1992). VCs recognize that the success of a fund today leads to more investments from limited partners tomorrow and the reputation among limited partners is a crucial competency for VCs. With the pressure on successful performances within the fixed duration of periods, it is reasonable that investors are steered towards less risky innovations that require shorter commitment (Lerner, Schoar et al. 2007, Budish, Roin et al. 2013, Budish, Roin et al. 2015). Moreover, a typical VC has a few partners who individually seek an investment opportunity but collectively make decisions on which venture to invest in. Since a partner whose reference is accepted among colleague partners may enjoy individual perks or monetary merits, each partner has to provide convincing evidence to persuade other partners (Wu 2015). The possibility of moral hazard residing in the collective decision making structure, with costly information acquisition about young innovations, promotes investors to favor less risky investment opportunities.

To sharpen these above arguments and derive testable hypotheses on the impact of the valuation challenge on the nature of innovations backed by VCs, consider a simple model as follows. Assume that there are two types of technologies: technology H and technology L. Technology H is developed from scratch and, thus, lacks prior art, while technology L builds upon a series of similar technologies and well-established knowledge base. Naturally, technology H is an example of a high-risk-high-return type innovation,

whereas technology L has less risk and less expected returns ($V_H > V_L \; and \; r_H \geq r_L$). Commercialization process of both types of technologies consists of two phases: early-stage R&D and advanced-stage R&D. Early-stage R&D includes experiments for the purpose of identifying opportunities and producing a prototype product, whereas late-stage R&D is designed to advance the prototype technology to finally confirm the commercial feasibility proposed at an early-stage R&D stage. Let $I(1+r)$ be an outside option available for investors, where I is an endowment for investment and r is an interest rate.

Note that this model addresses two different types of risk. On one hand, high-risk-high-return innovation is incorporated with scientific uncertainty, and hence higher likelihood of failure, as denoted by r_i . On the other hand, technology H also suffers from another source of uncertainty associated with valuation. Because of the lack of precedence and the hidden nature of information, investors financing disruptive and revolutionary products are exposed to higher noise level in verifying the prospect of a project. $\rho_H \geq \rho_L$ implies that the valuation challenge at an early stage disproportionately hampers the value of high-risk-high-return type recognized by VCs. In other words, the information of the value of type H innovation faces more discount rate due to the high information friction. This valuation uncertainty disappears in advanced development stage, reflecting that a series of trials and errors accumulated throughout early development stage helps VCs better estimate the prospect of both innovations in late development stage.

[Insert Table 1. Summary of Proposed Model here.]

We summarize the situation in Table 1 above. Assume that a VC is given the two investment choices in the late stage where neither technology A nor B has information friction. A VC makes investment decisions if and only if doing so promises more profits than $I(1+r)$. Where both investment options promise greater expected profit than the outside option, the investor will decide which technology to finance, depending on a simple calculation of expected returns. Specifically, a VC will choose the high-risk type innovation as long as

$$(1-r_H)V_H \geq (1-r_L)V_L > I(1+r)$$

A bottleneck here occurs when the type H technology that would be otherwise financed by the VC does not make all the way to the advanced development stage because of a high discount rate at early stage.

$$I(1+r) < \rho_H(1-r_H)V_H < \rho_L(1-r_L)V_L$$

If type H innovation faces harsher discount rate at early stage as below, a group of investors who potentially enter to the venture financing market might not even decide to do so.

$$\rho_H(1-r_H)V_H < I(1+r) < \rho_L(1-r_L)V_L$$

The simple framework shows that some VCs may have incentives to invest in technology A if investing in the breakthrough innovation at a late R&D stage brings more expected returns than investing in an incremental counterpart or in an outside option. Obviously, however, technology A cannot make it to the advanced development stage unless it gets funded at an early stage first. It suggests that VCs are more likely to invest in type H innovation if ρ_H – the low level of information transferability – decreases.

Would an innovator independently moderate ρ_H? In fact, the question has received much attention from practitioners and researchers. Startups can address the problem by running a small market test at an early stage and incrementally improving the quality of existing product reflecting the market test outcomes, because it is crucial for a startup to generate the "proof-of-concept" of a technology as early as possible to receive full consideration from VCs. The strategy is also known as the "lean startup approach" and is documented by a series of research (Ries 2011, Marx, Gans et al. 2014).

However, the lean approach is not applicable in some high-tech sectors that are heavily regulated, that disrupt existing market segments or that require heavy investment for mass-production. For example, the pharmaceutical industry is governed by strict regulations to guarantee the safety and the efficacy of drugs and here lean-testing might not be feasible given regulatory oversight and also because animal and human trials involve their own complications. It is an irony that it is not practicable for startup innovators to adopt a "lean startup approach" in many high tech sectors where startups need it most.

Moreover, it is the high-tech industries where the underinvestment of radical technologies raises greater concerns.

One possible response to the underfinancing of exploratory innovations is for a public intervention to avail information on the underserved innovations up to the extent that private sector can reasonably estimate the commercial and scientific viability. There is long historical strand of prior work on the impact of public policies on the growth of basic science that would otherwise attract few funding from private sector (Nelson and Winter 1977, Dosi, Freeman et al. 1988). In the context of entrepreneurial financing, governments of many countries have allocated a significant share of public resources to fund technologies that they believe are not financed otherwise (Lerner 1996, Jeng and Wells 2000).

Our goal is to find empirical evidence on whether a regulatory change promotes investors to support uncertain technologies that are not financed otherwise, by decreasing the level of ρ_H. The stylized set up above lends itself to two testable hypotheses. First, as investors are capable of estimate the value of young technologies with the decreased ρ_H, more investors will pursue financing early-stage innovations.

Hypothesis 1.1. VCs are more likely to invest in early-stage innovations when a regulatory shift discloses more information associated with technologies at an early stage.

Second, the theoretical framework above indicates that, as long as an innovation has precedence such as market performances of similar ones as shown in the case of type L innovation, VCs will support the technology regardless of the size of ρ_H, whereas innovations with higher uncertainty are disproportionately underfinanced. VCs then have to compete with the limited source of "well-known" innovations, ignoring potentially promising opportunities from the group of innovators with little precedence (Murray and Marriott 1998, Hochberg and Rauh 2012). While the underserved group may have different definitions including incomes, races and genders, this study uses geographic variation as a proxy of innovation with little visibility. It reflects that VCs are often herded into financing ventures in the US, mostly in Silicon Valley and Massachusetts, while other regions have

not lived up to the availability of venture funding in North America in spite of considerable public and private efforts (Lerner, Schoar et al. 2007, Lerner 2009).

Hypothesis 1.2. The tendency that VCs invest more in innovations at an early stage as a response to the regulatory shift appears more salient among a group of innovations that has higher uncertainty due to their geographic location – i.e. the group of Type H innovations.

2.2. Financing of Risky Innovations and Syndication of VC Investments

As VCs' investment focus switches toward young and risky innovations, the next question is how the investors deal with the higher level of uncertainty inherent in the exploratory innovations. Note that our stylized setup specifies two types of risks, one on high scientific uncertainty (r_H) and the other on information friction (ρ_H). The fact that a policy shift potentially ameliorates the valuation problem with regards to ρ_H does not necessarily means that it reduces the considerable risks in terms of funding and managing risky and nascent innovations.

One possible change in VCs investment strategies is that the investors tend to syndicate their investment in order to diversify the investment portfolio. Prior work has documented the rationale behind syndication of investments (Gompers and Lerner 2000, Jääskeläinen, Maula et al. 2007, Dushnitsky 2012). A VC can enter into a round as a single investor. Alternatively, it can form a consortium with other investors to invest in a round as a group. A benefit of having co-investors in an investment round is that the group investment increases the total amount of investment in a round without putting too much risk to a single investor. In other words, an investor can diversify portfolios, by participating in syndicated investment opportunities.

Specifically, syndication is a suitable tactic to fund early-stage innovations. A VC can fund several "options" at an early stage, investing in a reasonable amount in each, and monitor the progress of investees to determine to which startups it will make additional investments (Bergemann and Hege 1998, Li 2008). As a focal regulation pushes the trajectory of VC investments toward technologies with greater uncertainty, VCs are

expected to adopt the "real option strategy" with more frequent use of syndication (Carlsson and Fullér 2003, Yeo and Qiu 2003, Li 2008).

Our simple framework justifies the increasing use of syndication by VCs followed by changes in the types of VC-backed ventures. Where ρ_H is considerably high, available investment options are limited to outside option ($I(1+r)$), early-stage type L innovations ($\rho_L(1-r_L)V_L$) and/or advanced-stage type L innovations ($(1-r_L)V_L$). The benefit of syndication - decreases portfolio variance – is described in the simple variance formula below.

$$Var(H+L) = Var(H) + Var(L) + 2\,Cov(H,L)$$

If two assets are uncorrelated, the level of decrease in portfolio variance, as opposed to the variance of single asset, depends on the difference between variances of two assets. In the case of type L innovation, ρ_L is close to 1 and, thus, the level of risks of assets available in the market is not significantly different. Therefore, there is no clear merit to include two similar assets to an investment portfolio. It suggests that a VC may decide to focus on one or a few assets as a sole investor, rather than syndicating one investment to make use of limited endowment to diversify a series of investment opportunities. When some investors are more likely to fund type H innovations responding to a policy shift, however, variances of assets existing in the market become more diverse, indicating that the advantage of diversifying portfolio becomes greater.[2]

Hypothesis 2. VCs are more likely to invest in a team, rather than investing in a round alone, as the regulatory shift induces the investors to take greater level of risks

Finally, we investigate how changes in the nature of VC-backed ventures affect the investors' investment performances. According to our model, VCs choose to invest in type

[2] The benefit of decreased portfolio variance also depends on the covariance among included assets. Estimating how the distribution of covariance among assets change as a result of the availability of high-risk-high-return assets is, however, far beyond the scope of this model. Instead, the argument assumes that a VC can find two or more uncorrelated assets regardless of the policy shift.

H innovation only if the increase in ρ_H allows investors correctly estimate that type of innovation promises greater profits than type L counterpart.

$$(1 - r_H)V_H > \rho_H(1 - r_H)V_H > \rho_L(1 - r_L)V_L$$

However, it may not necessarily be true. What the model implicitly assumes is that the increase in ρ_H led by a policy shift is just enough for VCs to make fully-informed decisions in investing in young technologies as a result of a policy shift. Instead, the institutional change may increase ρ_H too high so that the investors inappropriately and light-heartedly invest in ventures more affected by the intervention. Thus, it is possible for some VCs to finance the companies developing type H innovations without carefully examining the prospect of the new technologies. The two situations posit different implications on how we think about the economics behind the effects of the ODA.

Then how do we know whether VCs make rational investments depending on a greater amount of information or merely speculate on technologies at nascent stage as a result of a policy shift? One possible way is to compare the outcomes of investments made after the change to those prior to that. If the policy shift indeed makes credible information available, VCs should not face significantly worse performances as a result of investing in technologies at earlier stage or with higher uncertainty. Alternatively, VC-backed startups should yield worse exit performances if the policy shift has no impact on information disclosure but rather leads to speculation of VCs. We test these ideas using *Hypothesis 3* from above in a formal econometric setting in what follows.

Hypothesis 3. Exit performances of VC-funded startups remain stable regardless of changes in the timing of VC investments, if a policy shift helps VCs correctly value the prospect of risky and nascent innovations.

3 Empirical Context: Orphan Drug Act (ODA)

The biotechnology industry is an ideal setting for this study as entrepreneurial firms and venture capital funding are the leading source of technological advancement in this field (Moeen 2013, Chatterji and Fabrizio 2014, Howell 2015). Innovations in this area

many scholars have argued have significantly improved health and social welfare, but the risks of investing in early stage technologies are not negligible (Pisano 2006). Only less than 18% of drug molecules tested in clinical trials make it all the way to market with recent estimates suggesting that the R&D costs of getting a new molecule to the market is upwards of USD 2.7 billion (DiMasi, Grabowski et al. 2016, Kim 2016) . One important issue relatedly is that, while it usually takes more than 10 years to get a new drug approved, most funds managed by VCs have shorter lifespans – i.e. 8 to 10 years. In fact, biotech startups and VCs have expressed concerns about the long period required for drug commercialization (Budish, Roin et al. 2015).

To briefly introduce the drug approval process, it typically takes 12 to 18 years for a therapeutic molecule to obtain marketing approval from a regulatory agency such as the Food and Drug Administration (FDA) in the US or the European Medicine Agency (EMA) in the EU. A drug developer first identifies a therapeutic molecule or a target that may treat one or multiple disorders. It takes 2–8 years to optimize a lead molecule and conduct preclinical studies including animal studies to get an approval from a regulatory agency to test the drug candidate with human patients. Clinical trials consist of three phases. A Phase I study tests the general safety of a drug candidate with 20–100 healthy volunteers. A Phase II study validates the efficacy of a drug with 100–300 patients who suffer from an initially targeted disease. Finally, in a Phase III trial, trial sponsors perform randomized and controlled multicenter trials to finally confirm the safety and efficacy of a drug with 1,000–3,000 patients. Each phase takes approximately 1.5 years, 2 years, and 3 years, respectively. When a drug has undergone all the clinical studies, the developer then submits a New Drug Application (NDA). It takes a year for FDA to review all the procedures and the outcomes to finally approve the marketing of a drug. Failure rate is considerably high in this sector. Only 16% of drugs tested in clinical trials successfully reach to the approval stage (Kim 2016).

ODA was first enacted by the US in 1983 to facilitate the development of treatments for rare diseases (Rohde 2000, Grabowski 2005). In the past, most rare diseases remained "orphans" because market sizes were too small to justify the costly development of medications. To intervene in this market failure problem, the policy provided orphan drug developers a variety of incentives, including 50% tax benefits associated with clinical trial

costs, regular guidance meetings with the FDA and market exclusivity for 7 years in the US and 10 years in the EU upon conditions. The considerable success of the act encouraged the EU and other countries to adopt similar legislation (Lichtenberg and Waldfogel 2003, Cheung, Cohen et al. 2004, Yin 2008). The EU's adoption of ODA in 1999 marked the greatest change since the enactment of ODA by the US. This study analyzes the impact of the enactment of ODA by the EU because there were only a few biotech startups or VCs heavily investing in the biotechnology sector when the US adopted the act in 1983.

Interestingly, many drug developers have used the act to showcase the prospect of novel drugs (Johnson 2014). An increasing number of small-sized drug developers develop breakthrough drugs as rare disease treatments first and then persuade large pharmaceutical partners with the test outcomes to expand the scope of the novel drugs to treat general diseases, increasing the propensity of licensing and enhance commercialization performances. Kim (2016) documents the example of Remicade™, one of the blockbuster drugs and, at the same time, one of the most successful orphan drugs. Remicade™ had initially attracted little attention from large pharmaceutical firms due to too huge risks associated with the breakthrough therapy. However, soon after it was successfully approved as a rare Crohn's diease, it received prospecting calls from large pharmaceutical partners and finally won more than 12 label expansions in a collaboration with Johnson & Johnson. The key underlying mechanism is that the small-scale clinical studies designed for rare disease treatments by regulatory agencies enable drug developers to provide credible "proof-of-concepts" of novel drugs, thereby improving the transferability of breakthrough innovations without conducting costly demanding Phase III trials. In this sense, the ODA creates a pathway for constructing a lean-startup and early testing in the context of bio-pharmaceutical innovation for rare diseases.

ODA affects the extent to which VCs are willing to take risks in several ways. First, the act directly increases the chances of achieving non-zero returns, by creating niche markets for rare diseases. Thanks to the market exclusivity given to the first treatment of a rare disease, an orphan drug developer can make profits, however small the rare disease indication market is. However, the creation of new market doesn't completely explain why VCs invest in nascent technologies to serve the market.

One explanation is that orphan drug designations from regulatory agencies may serve as a signal indicating that designated drug candidates have greater potential to treat general diseases beyond the scope of the initially approved rare disease market. Orphan designation is often considered a "golden badge" with which to receive a fast-track review from regulatory agencies and to get an easier approval. As long as USFDA or EMA have credible reputation among investors, a biotech firm can leverage the decision of agencies to better convince a VC firm of the prospect of its novel drug candidates by obtaining an orphan status. In other words, ODA transforms hidden information about the quality of novel drugs to observable information, thereby decreasing the cost of acquiring information necessary to make fully–informed decisions.

More importantly, ODA helps drug developers create more concrete information related to exploratory drugs, beyond merely helping them send a signal. When a drug candidate is designated an orphan status, a drug developer can test the molecule to clinical trials specifically designed for rare disease treatment. Similar to the usual clinical trial procedures, a developer of an orphan designated drug candidate should pass three phases of clinical trials to confirm the safety and the efficacy of the drug. By definition, however, rare diseases only affect a small number of patients that show peculiar patterns of malfunctions or impairment of bodies mostly due to gene mutations. It means that a drug developer can test the mechanisms and the efficacy of an orphan drug candidate in much smaller clinical setting with more homogenous group of patients. In other words, the orphan trials provide the chances for drug developers to showcase the prototype of novel drugs in a small market.

Finally, we stress that the original purpose of ODA has nothing to do with solving the underfinancing of novel innovations by VCs. A common caveat of a public policy analysis is that players affected by the act may behave strategically to the enactment of the policy shift. The endogeneity or reverse causality issue may mislead the pure causal impact caused by the public policy. Since ODA does not explicitly aim to but unexpectedly affect the underfinancing of risky innovations, we believe that those concerns are relatively relaxed when using ODA to study the direction of VC investments in the focal sectors we analysis.

4 Data

The primary source of our data is the *VentureXpert*™ database which has been used in some recent scholarly work (Dimov and Shepherd 2005, Dushnitsky and Lenox 2005, Dimov and De Clercq 2006, Hong 2013). We collect all investments from this database made over the globe between 1957 and 2015 in the medical/health/life science categories. The dataset includes 70,355 investments made by 4017 investing firms to finance 14,650 startups. We exclude some observations that do not disclose the information on explicit investment date, the stage of invested startups, the industry category and major characteristics of investing firms, leaving 56,760 investments ranging from 1971 to 2015 as our final dataset.

[Insert Table 2 here.]

Table 2 provides the summary statistics. An average fund participates in approximately 28 rounds. Given that the maximum number reaches 164, we note that the distribution of the size of VCs has long tails. A startup company generally receives 7 rounds of investment from 12 funds organized by 9 investors. Each round involves on an average $15 million, although the amount starkly varies over investing firm and investment stage. Typically, the amount given to early stage companies is smaller than that given to those at growth stage. Seed investments involve around $1 million per round and early stage investments $5 million on average. Seed and early stage investments account for approximately 30% of total investments made by VCs.

5 Identification Strategy

5.1. Method

We use a difference-in-difference (DiD) approach to study the impact of ODA on investment characteristics as well as performance. The idea is to measure the difference in outcome variables between the treatment group and the control group to tease out the causal impact of ODA from those that are possibly caused by other shocks that concurrently took place in 2000. To assign the treatment group and the control group, we exploit the fact that ODA disproportionately affects biotech firms developing drugs. Among the investments

falling in the category of medical/health/life science, thus, we determine the treatment group as a group of investments into companies investing in the following categories: Biotech-Human, Med/Health Products, Medical Diagnostics, Medical Therapeutics and Pharmaceutical. The control group is the set of investments in the medical/health/life science category but not directly related to developing the treatment for human disorders. The areas include Biosensors, Biotech Equipment, Biotech Other, Biotech Research, Biotech Animal, Biotech Industrial, and Med/Health Services.

Yet, one may question the effectiveness of comparability between drug-related biotechnology fields and non-drug related counterparts. Biotechnology fields closer to the pharmaceutical sector, for example, are significantly different form non-drug related fields regarding some major factors affecting VCs' investment decisions. To justify the comparability, we examine the evolution of VCs' investment patterns over time in both groups.

[Insert Figure 1 here.]

Panel A in Figure 1 compares the change in the percentage of early-stage deals in drug-related biotechnology fields to that in other biotechnology fields over time. Panel B plots the average days a startup takes to receive investments in drug-related fields and those in non-drug related counterparts. Both graphs show that non-drug related biotechnology fields are comparable to drug-related fields prior to ODA especially during the period after 1990 and before 2000. Moreover, the converging investment patterns in both groups begin to diverge around 2000, suggesting that ODA may lead to a causal impact on the early-stage investment decisions by VCs.

However, the pattern does not confirm that only ODA contributes to the diverging trend around 2000. If other major events disproportionately affecting drug-related biotechnology fields simultaneously took place around 2000 and significantly impacted the investment decisions by VCs, our setting may overestimate the magnitude of the pure causal impact of ODA. For example, a private company called Celera Corporation launched a gene-sequencing project in 1998 parallel to the Human Genome project, a government-led program. While the two projects were officially complete in 2003, a 'rough

draft' of the genome was finished in 2000 (Venter, Adams et al. 2001, Williams 2010). To investigate that these factors affect the direction of VC's investments in a similar manner as ODA does, we draw two graphs for the falsifications in Figure 2.

[Insert Figure 2 here.]

Panel A and Panel B in Figure 2 replicate the Figure 1 to show the composition of seed stage deals and late stage deals over time, respectively. If some environmental factors systemically impact the VCs' investment trend as a whole, we should be able to observe the similar diverging patterns around 2000 in either seed stage deals or late stage deals as they appeared in early stage investments of VCs. However, Figure 2 does not show such patterns neither prior to ODA nor after ODA as they appeared in early stage deals, indicating that the specific diverging trend found in Figure 1 only appear among early-stage investment deals of VCs. Still, this falsification does not take into account the possibility that some other factors only affect the early stage investments of VCs in a similar way that ODA does. While we try to minimize the impact by controlling year effect and industry effect, we admit that this would be one limitation of this study.

Another concern is that the composition of VCs may change after ODA. For example, some shocks around 2000 may induce the entry of new venture investors into the drug-related biotechnology sector. Then our DiD method only captures the impact of investment patterns of entrant VCs different from incumbent VCs, but not the changes of existing players caused by ODA. To take this situation into account, we report both OLS and fixed effect model.

5.2. Estimation and Variables

The unit of analysis is a round investment. To formalize the DiD method and to facilitate statistical interference, we estimate the following equation:

$$Y_{ijt} = \alpha_j + \gamma_t + X_i'\eta + \beta_0 Drug_{ij} + \beta_1 AfterODA_{it} + \beta_2 Drug_{ij} * AfterODA_{it} + \varepsilon_{ijt}$$

where Y_{ijt} represents the outcome variable (the timing of investment, the location of investees, the number of investors per round, and the exit performance), i indexes individual round investments ($i \in \{1, ..., 56760\}$), j indexes industry categories ($j \in \{1, ...,12\}$), and t indexes the year ($t \in \{1957, ..., 2015\}$). *AfterODA* is a binary variable equal to 1 if a molecule entered after 2000 and 0 otherwise. *Drug* assigns 1 to the group of investments made to drug-related startups and 0 otherwise. C_i is a vector of control variables. Errors are clustered at the technology category level.

The coefficient of interest is b_2. The coefficient captures the difference in the outcome variables of the treatment group relative to the control group. b_0 and b_1 explain any effect caused by shocks specific to the drug-related categories and by the shocks that occur concurrently with the ODA in 2000, respectively. We include industry category specific dummy variables, investing firm dummy variables and year dummies to control for unobserved heterogeneity at various levels.

For an in-depth analysis, we also use a triple DiD method as below. With a triple difference estimator, for example, we compare the evolution of the gap between investments in drug-related biotechnology areas and those in other biotech-related areas among the group of early-stage investments to the evolution of the gap between drug-related investments and non-drug related counterparts among the investments occurring at expansion or later stage. The triple DiD estimated formula is as follows:

$$Y_{ijkt} = a_j + g_t + X_i'm + b_0 Drug_{ij} + b_1 AfterODA_{it} + b_2 EarlyStage_{ik} + b_3 Drug_{ij} * AfterODA_{it} + b_4 Drug_{ij} * NovelMOA_{ik} + b_5 AfterODA_{it} * EarlyStage_{ik} + b_6 Drug_{ij} * AfterODA_{it} * EarlyStage_{ik} + e_{ijkt}$$

where $EarlyStage_{ik}$ is an indicator variable that equals 1 if an investment is made at an early stage round and 0 otherwise. Investor and startup controls are included. I run an OLS model with dummy variables to estimate the regressions.

To test *Hypothesis 1.1* on the timing of VC investments, we use two outcome variables. The first measurement is a binary variable that equals 1 if a fund invests in an

early-stage startup and 0 otherwise. Second, we also measure the days a startup takes to receive an investment. For testing *Hypothesis 1.2* on the switch from the US-based startups to those in relatively underserved regions, we investigate if a VC finances an EU-based startup compared to an US-based startup. We use a binary outcome variable that assigns 1 to the group of investments to EU-based startups and 0 otherwise. To observe the syndication pattern of VCs in *Hypothesis 2*, we count the number of investors participating in a single round. As a complement, we also look at changes in the amount invested by a single VC. Lastly, to study the investment performances of VCs with *Hypothesis 3*, we exploit several binary variables to estimate both successful startup performances and failures. First, the M&A variable is a binary one equals to 1 if a VC-backed startup exits through acquisition. Second, the binary variable named IPO indicates whether a startup exits through initial public offering (IPO) or not. Lastly, a binary variable called Bankruptcy assigns 1 if a startup reports bankruptcy or it is defunct and 0 otherwise.

Finally, we note that measuring the impact of ODA on investment performances is challenging because startups founded prior to 2000 may continue to receive investments after 2000, possibly for advanced-stage rounds. To avoid such confusion, we restrict our samples to early stage investments only and compare the exit performances of early-stage startups invested for the 5 years prior to ODA to those invested for the 5 years after ODA. Note that, because of the sample restriction, the final sample for *Hypothesis* 3 significantly reduces from 57,000 to 4,500. We do robustness checks by changing the size of window from 3, 5, and 7 and it does not change the nature of results.

6 Results

6.1 Types of Ventures Invested by VCs

[Insert Table 3 and Table 4 here.]

We find evidence in favor of *Hypothesis 1.1*. Table 3 presents the results on the analysis on timing of investment by VCs. After controlling all time and industry fixed effects, the interaction coefficient are positive and statistically significant across all regressions from Column (1) to Column (2). Specifically, in technology fields affected by

ODA, the propensity that a VC invests in an early-stage startup increases by 3% in the most conservative specification. Alternatively, Column (3) and Column (4) measures the time difference between a startup's foundation date to the date it receives a funding as dependent variables. Both tables report that, in ODA affected areas, VCs invest in startups at least 1 year earlier than they do in control areas.

As predicted in *Hypothesis 1.2*, VCs are more likely to invest in early-stage startups from previously underinvested regions in ODA affected areas. Column (1) Table 4 shows that the investors are 2.5% more likely to invest in early stage startups from European countries. Meanwhile, the probability that VCs seek late stage deals from Europe decreases by the same magnitude. Also, according to the triple interaction terms in Column (1) and Column (3), the increase in financing early stage startups and the decrease in financing late stage startups appears more drastically among EU-based VCs. As shown in Column (2) and Column (4), US-based VCs do not show the systemic and statistically strong patterns.

One possible interpretation of these results, consistent with the evidence of *Hypothesis 1.1* is that VCs are reluctant to seek for early-stage innovations in the EU because of higher uncertainty. Equity-based entrepreneurial financing system is not as established in the EU as in the US, which may create more noises when valuating highly risky innovations. Moreover, it is the group of EU-based VCs that strongly respond to the policy shift. It suggests the following two scenarios. First, even European investors had previously sought early stage investment opportunities outside the EU, mostly in the US, to avoid the extra cost of valuing technologies at a nascent stage in the European market. Second, to avoid the unnecessarily high risk associated with financing early stage deals in the EU, VCs from the region only finance less risker late stage deals. However, as the EU ODA provides both a signaling and a means for European biotech firms to provide more convincing information on technologies at an early stage, the focus of EU-based VCs springs back to source promising early stage innovations in the European market. Taken together, Table 3 and Table 4 verify that VCs are more likely to invest in innovations at nascent stage and the response to ODA appears more prevalently in regions that have relatively underserved by VCs.

6. 2 Changes in Investment strategies of VCs

[Insert Table 5 here.]

We find evidence that investors are more likely to syndicate deals with other investors. Table 5 reports the increase in the number of investors per round and the decrease in the average amount invested by each VC in a round. In ODA affected areas, a deal involves 0.26 more investors on average, as opposed to a deal in less affected areas. As a round investment includes more investors, the amount invested by a single investor decreases by $1.3 million.

An interesting pattern is that the syndication strategy of VCs moves varies over the stage of investment deals. In Column (2) where we restrict the sample to early stage investment only, the number of investors participating in a round decreases by 1.5. The pattern becomes reverse for late stage deals in Column (3). The triple DiD regression reported in Column (4) reconfirm the diverging patterns. In other words, VCs increasingly seem to run as a team. The investors individually seek for early stage innovations and then syndicate investments to finance a few promising startups that reach for late stage rounds in a team. Such an individual sourcing and collective investment decision has been a typical organizational structure of a VC. Interestingly, the organizational structure of an individual VC seems to extend to the collective investment behaviors of VCs as a whole. It implies that ODA induces VCs to cooperate as a group of investors than a group of individual investing firms. The pattern is consistent with the predictions from real option theory (Myers 1977, Carlsson and Fullér 2003, Yeo and Qiu 2003).

6. 3 Performances of VC-backed Companies

[Insert Table 6 here.]

Table 6 provides the results of the analysis on exit performances of VC-backed companies. The coefficient of interaction term in Column (1) and Column (4) is negative and statistically significant, which implies that the propensity of M&A decreases by 11% and 14% as a result of ODA. But, at the same time, the propensity of IPO increases by 17%

and 15% in Column (2) and Column (5), respectively. Column (3) and Column (6) show that ODA doesn't seem to affect the probability of bankruptcy of VC-backed companies.

Taken together, biotech startups invested after ODA show slightly better exit performances than those invested prior to ODA. But their exit modes change from M&A toward IPO. What lead to the changes? While answering the question is outside the scope of this study, it is possibly related to the capabilities of biotech firms with which to individually advance its drug molecule to advanced stage. When a biotech firm is not capable of managing later-stage development, IPO is not a viable option. Sales of stock to the public require a thorough level of due diligence that guarantees a reasonable level of revenue streams in the close future. Instead, they would sell molecules to large pharmaceutical firms at earlier stage, making M&A as optimal exit modes. The situation may change, as an entrepreneurial drug developer is enabled to commercialize its drug independently or at least to run some clinical trials alone to prove the safety and the efficacy of the drug (Kim 2016).

7 Conclusion

VCs are considered to invest in innovations at nascent stage, which inherently incorporates huge risks. Because it is difficult to value the prospect of novel technologies at early development stage, however, VCs may be herded to finance advanced-sage projects for which an archive of scientific knowledge and commercial performances is available. An institutional change can steer the investors toward supporting new innovations at early stage, by providing more information necessary to value the young projects. In the context of ODA, we find that VCs are more likely to invest in early-stage technologies. To reduce the risk of failure, moreover, the investors invest in a team rather than putting a huge amount into a company alone. Finally, we document that the exit performances of VC-backed startups do not get worse as a result of VCs investing into early-stage innovations. It suggests that VCs are enabled to make fully-informed decisions thanks to information provided by ODA, rather than bet on risky and highly uncertain projects.

To the best of our knowledge, this study is one of the first studies to empirically report the impact of valuation challenge on the investment decisions of VCs, contributing

to the literature on the determinants of entrepreneurial financing and their implications on the types of technologies that receive the investments. The results of this paper suggest that the availability of a small market test caused by a policy shift leads VCs to better examine the ideas of exploratory technologies and, thus, to finance the nascent innovations pushing the scientific frontier. In addition, this study documents the syndication strategies of VCs to finance technologies at an embryonic stage but still to avoid high uncertainty associated with the innovations.

Our findings also have several policy implications. It is often one of top priority for a country to establish a solid ecosystem for entrepreneurship. Because the shortage of necessary entrepreneurial financing occurs at fairly nascent stage, however, it is often not enough to financially subsidize VCs. Rather, a government effort should be used to minimize a market failure that an individual investor or a startup cannot deal with. Information friction is a crucial problem in the sector where the potential of an early-stage innovation is not verifiable. Where startups cannot communicate the genuine value of early stage innovations, these firms can be disproportionately underfinanced compared to other startups of which projects depend on existing scientific base. Even worse, the situation may affect the incentives of startups to pursue the high-risk-high-reward type of innovations, thereby slowing the innovation cycle. Rather, a policy can earmark entrepreneurial firms promoting promising technologies at early stage or help them develop those technologies up to the level that they can bring credible evidence to investors. This study traces how an institutional change encourages VCs to invest in early-stage technologies without decreasing the prospects of the investments. Thus, our findings can aid policy makers design an environment that pushes the trajectory of private VC investments toward breakthrough innovations (Lerner 1996, Lerner 2002).

A final word on the role of ODA in incentivizing pharmaceutical innovation might be merited. This particular aspect of policy tools used with ODA has been much discussed in the literature, but what has potentially been left unexplored is the channel or mechanism through which entrepreneurial start-up firms scale up on innovation with regulation. To the extent that our results show a contribution of better matching of investor-investee linkages, we are potentially contributing by showing how regulation can stimulate innovation through the entrepreneurial financial markets.

This project still leaves some rooms for future studies. First, while this paper reports that VC's investment focus switches back to early-stage and more uncertain innovations in areas affected by ODA, the management of early-stage investments may require different strategies than those to deal with late-stage investments. In fact, early-stage VCs starkly differ from late-stage VCs in terms of management styles. Some early-stage VCs directly run accelerators. The governance or investment structure of early-stage VCs may possibly be closer to that of individual angel investors rather than equity-based institutional investors focusing on late-stage deals. In the similar context, it is worth studying the changes in contract features as more VCs enter to serve previously underserved regions or finance technologies at the frontier. Also, the tendency toward financing risky innovations may vary over characteristics of VCs such as reputation or previous experiences in relevant markets. Related to this, while we try to tease out the causal impact of ODA, it is still possible that the group of startups in drug-related biotechnology fields may differ from the group in non-drug-related fields in some unobservable ways, which calls for the use of more sophisticated matching mechanisms.

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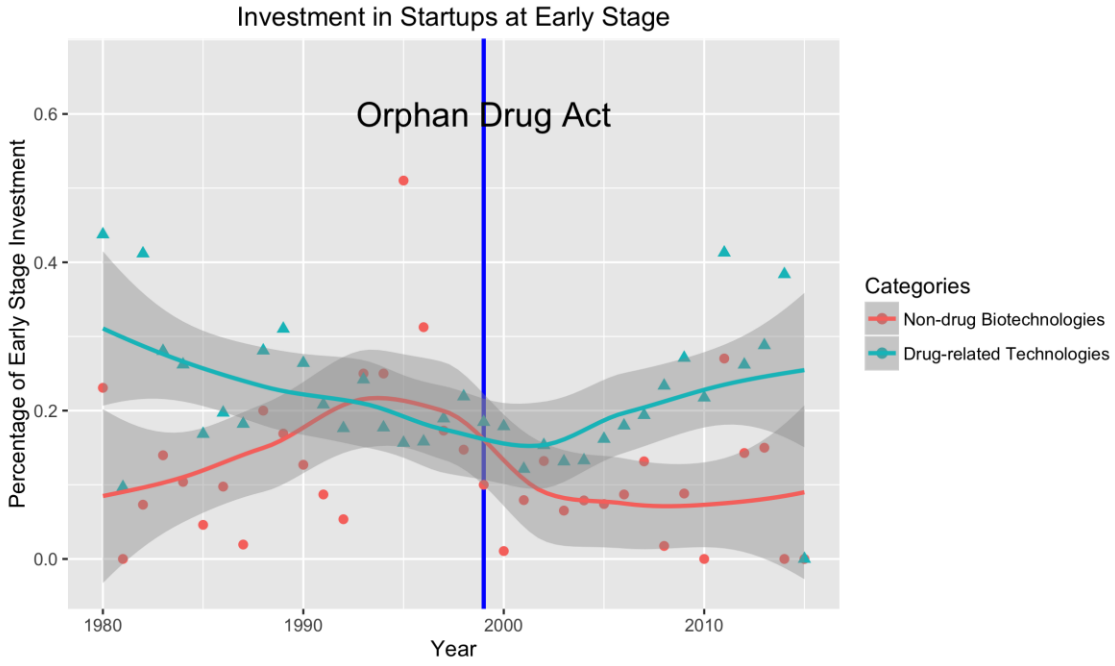
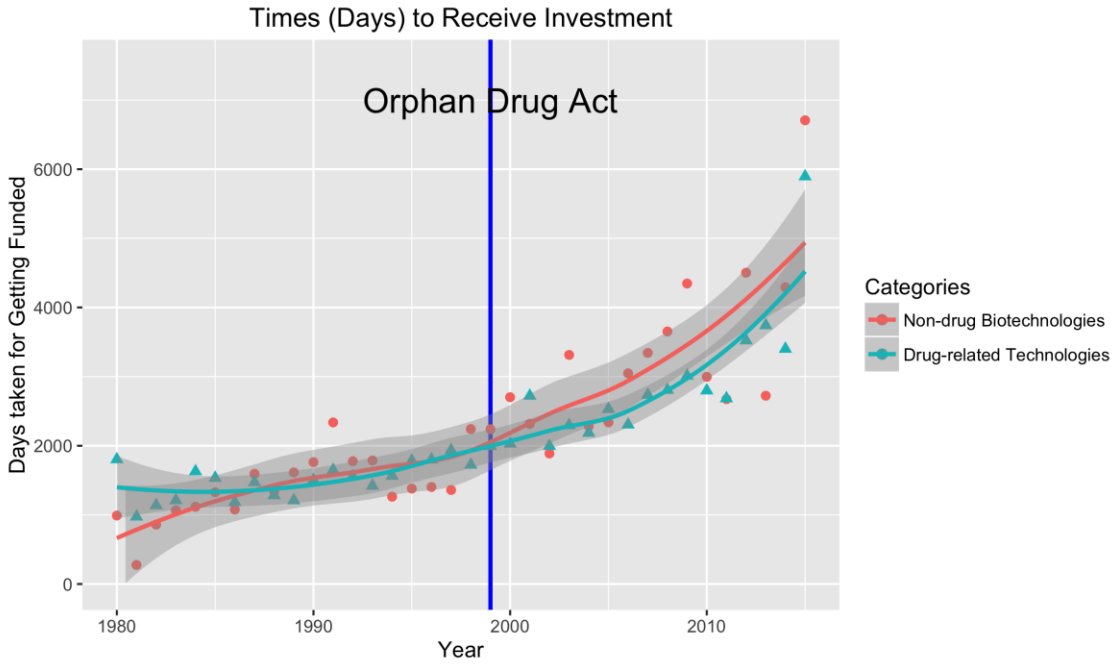
Figure 1 Orphan Drug Act and Timing of VC Investments

Panel A. Investments in Early Stage Startups



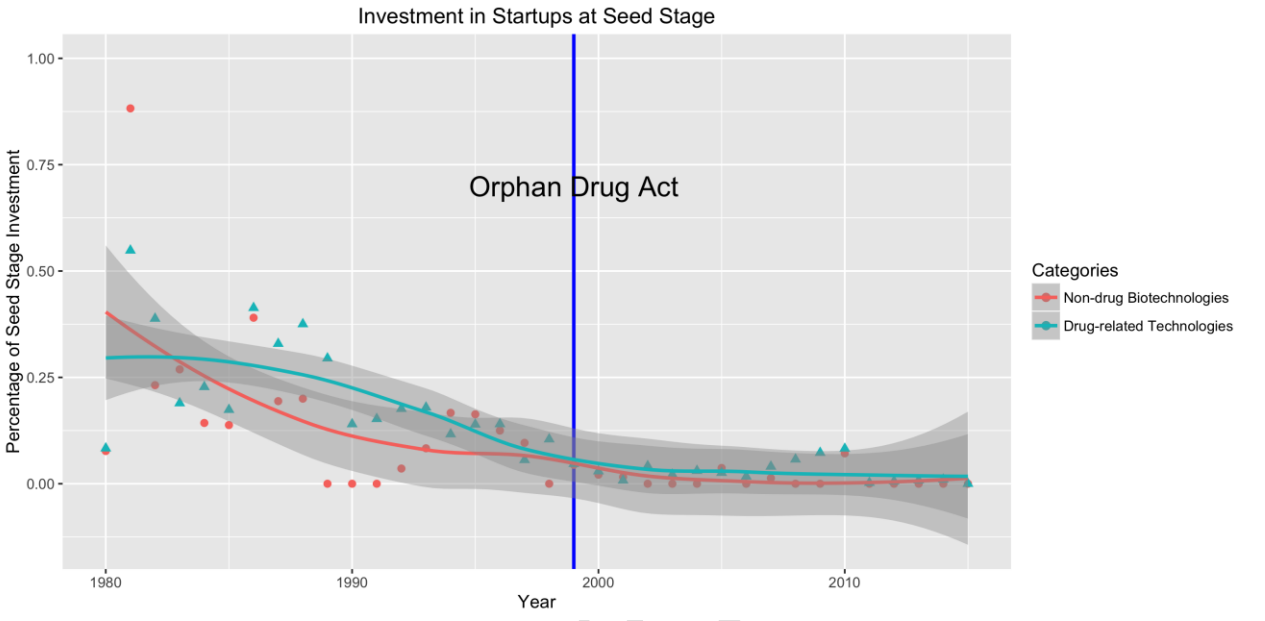
Panel B. Time to Receive Investments



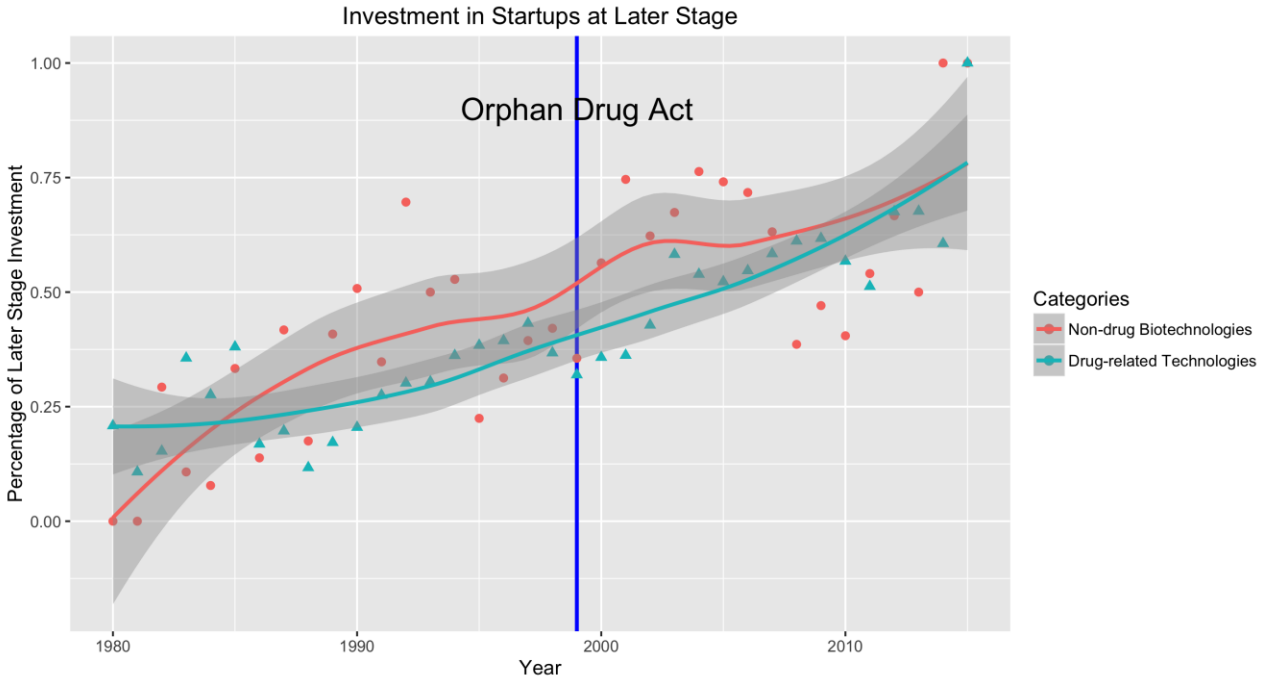
Notes: Panel A compares the change in the percentage of early-stage deals in drug-related biotechnology fields to that in other biotechnology fields over time. Panel B plots the average days a startup takes to receive investments in drug-related fields and those in non-drug related counterparts. Both graphs suggest that non-drug related biotechnology fields are comparable to drug-related fields prior to ODA.

Figure 2 Falsification: Investments in Startups at Other Development Stages

Panel A. Investments in Startups at Seed Stages



Panel B. Investments in Startups at Later Development Stages



Notes: Panel A and Panel B replicate the Figure 1 to show the composition of seed stage deals and late stage deals over time, respectively. Both graphs do not show systemic patterns neither prior to ODA nor after ODA as appeared in Figure 1, indicating that the specific patterns found in Figure 1 only appear among early-stage investment deals of VCs.

Table 1 Summary of Proposed Model

	Technology H	Technology L
Early stage	$\rho_H(1-r_H)V_H$	$\rho_L(1-r_L)V_L$
Advanced stage	$(1-r_H)V_H$	$(1-r_L)V_L$

Table 2 Descriptive Statistics

Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Total # of Rounds a Fund Participates in	56,760	27.585	21.564	1	164
# of Rounds a Startup Receives	56,760	7.096	4.052	1	27
# of Firms Invested in Startup	56,760	9.333	5.932	1	33
# of Funds Invested in Startup	56,760	12.230	8.321	1	49
Round ID	56,765	4.038	2.925	1	26
Amount invested in Round ($1K)	56,765	15,238.490	10,490.130	1	32,572
Number of Investors in Round	56,765	4.898	3.588	1	27
Amount invested in ID ($1K)	56,765	12,877.610	10,180.590	1	32,572
Year	56,765	2,002.595	8.244	1971	2015
Drug-related	56,765	0.802	0.398	0	1
Investment after ODA	56,765	0.707	0.455	0	1
Seed Stage	56,765	0.110	0.312	0	1
Early Stage	56,765	0.221	0.415	0	1
Later Stage	56,765	1.401	0.490	1	2
Private VCs	56,765	0.906	0.292	0	1
Corporate VCs	56,765	0.061	0.239	0	1
Angel Investors	56,765	0.002	0.050	0	1
Government VCs	56,765	0.009	0.094	0	1
Startups in EU	56,765	0.130	0.336	0	1
Startups in North America	56,765	0.830	0.375	0	1
Days to Investment	56,765	2,174.824	1,927.594	0	16,414
Amount invested in Round by each investors ($1K)	56,765	4,192.923	5,626.875	0.435	32,551.000
M&A	56,765	0.313	0.464	0	1
Bankruptcy	56,765	0.075	0.263	0	1
IPO	56,765	0.223	0.416	0	1
Investors in EU	56,765	0.137	0.344	0	1
Investors in US	56,765	0.676	0.468	0	1

Table 3 Timing of VC Investments

	Dependent Variables			
	Early stage		Time to investment (Days)	
	OLS	*Fixed Effect*	*OLS*	*Fixed Effect*
	(1)	(2)	(3)	(4)
After ODA	0.185	0.074	3,552.154***	4,335.053***
	(0.148)	(0.160)	(647.159)	(624.073)
After ODA X Drug-related	0.051***	0.036***	-696.178***	-367.410***
	(0.010)	(0.010)	(41.585)	(40.854)
Drug-related	0.034	-0.244***	567.721	1,005.061***
	(0.146)	(0.056)	(636.321)	(216.706)
EU	0.038***	0.071***	-113.159***	-461.891***
	(0.010)	(0.017)	(43.363)	(65.423)
North America	0.022**	0.040***	-241.650***	-317.163***
	(0.009)	(0.015)	(39.163)	(57.580)
VC	-0.021*		-175.754***	
	(0.012)		(52.202)	
CVC	-0.004		-213.342***	
	(0.014)		(59.873)	
Angels	0.146***		-1,085.800***	
	(0.037)		(159.988)	
GVC	-0.096***		126.589	
	(0.022)		(94.597)	
Category FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Investor FE	NO	YES	NO	YES
Observations	56,765	56,765	56,765	56,765
R^2	0.242	0.132	0.621	0.388
Adjusted R^2	0.241	0.072	0.621	0.346

Note:	*Investment round-level observations. Errors are clustered at the technology category level.* $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 4 Changes in the Regional Focus of VCs

	Dependent Variables			
	Investment into EU-based Startup			
	Early Stage Deals		Late Stage Deals	
	(1)	(2)	(3)	(4)
After ODA	0.058	0.224	0.094	0.298***
	(0.173)	(0.216)	(0.087)	(0.106)
Drug-related	0.201	0.133	0.132	0.049
	(0.170)	(0.211)	(0.085)	(0.103)
EU Investors	0.618***		0.455***	
	(0.042)		(0.019)	
US Investors		-0.188***		-0.137***
		(0.027)		(0.012)
After ODA X Drug-related	0.024*	0.037	-0.022***	-0.086***
	(0.014)	(0.031)	(0.006)	(0.014)
After ODA X EU Investors	0.157***		0.319***	
	(0.046)		(0.021)	
Drug-related X EU Investors	-0.150***		-0.045**	
	(0.045)		(0.021)	
After ODA X Drug-related X EU Investors	0.088*		-0.053**	
	(0.049)		(0.023)	
After ODA X US Investors		-0.203***		-0.292***
		(0.032)		(0.014)
Drug-related X US Investors		-0.016		-0.023*
		(0.029)		(0.014)

After ODA X Drug-related X US Investors		-0.004		0.095***	
		(0.035)		(0.016)	
Category FE	YES	YES	YES	YES	
Year FE	YES	YES	YES	YES	
Investor Controls	YES	YES	YES	YES	
Observations	12,558	12,558	44,207	44,207	
R^2	0.594	0.377	0.554	0.347	
Note:					*p<0.10; **p<0.05; ***p<0.01

Table 5 Syndication of VC Investments

	Dependent Variables				
	Number of Investors Per Round				Average Amount By Each Investor ($K)
	Total	Early Stage	Late Stage	Triple DiD	
	(1)	(2)	(3)	(4)	(5)
After ODA	1.970		1.842	1.801	-1,667.578
	(1.269)		(1.389)	(1.264)	(2,651.847)
Drug	0.801*	1.328***	1.533**	0.507	-738.618
	(0.441)	(0.344)	(0.620)	(0.441)	(925.608)
Early				-0.807***	860.182***
				(0.134)	(281.438)
EU Startup	0.444***	1.059***	0.301**	0.494***	-1,220.506***
	(0.133)	(0.275)	(0.153)	(0.133)	(277.950)
US Startup	1.578***	1.305***	1.707***	1.598***	-2,881.482***
	(0.117)	(0.250)	(0.134)	(0.117)	(244.612)
After ODA X Drug	0.267***	-1.156***	0.581***	0.540***	-1,304.663***
	(0.083)	(0.178)	(0.095)	(0.090)	(189.167)
After ODA X Early				0.293*	-665.040*
				(0.176)	(368.303)

Drug X Early				0.862***	-728.567**
				(0.151)	(317.173)
After ODA X Drug X Early				-1.203***	817.897**
				(0.194)	(406.256)
Category FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Investor FE	YES	YES	YES	YES	YES
Observations	56,765	12,558	44,207	56,765	56,765
R^2	0.270	0.387	0.295	0.276	0.277
Adjusted R^2	0.219	0.280	0.237	0.226	0.227
Residual Std. Error	3.170 (df = 53085)	2.570 (df = 10695)	3.256 (df = 40818)	3.158 (df = 53081)	6,622.427 (df = 53081)
Note:					*p**p***p<0.01

Table 6 Exit Performances of Early-stage Startups Invested by VCs

	Dependent Variables					
	M&A	IPO	Bankruptcy	M&A	IPO	Bankruptcy
		OLS			*Fixed Effect*	
	(1)	(2)	(3)	(4)	(5)	(6)
After ODA	0.087*	-0.407***	-0.194***			
	(0.051)	(0.042)	(0.035)			
Drug	0.163**	0.481***	0.092**	0.070	-0.044	-0.113
	(0.067)	(0.056)	(0.047)	(0.119)	(0.099)	(0.085)
EU	0.218***	-0.085***	0.072***	0.120	-0.113	0.110*
	(0.038)	(0.032)	(0.027)	(0.087)	(0.073)	(0.063)
North America	0.259***	-0.092***	0.091***	0.120	-0.135*	0.128**
	(0.036)	(0.030)	(0.025)	(0.082)	(0.069)	(0.059)
VC	-0.013	0.056	0.012			
	(0.042)	(0.035)	(0.029)			
CVC	-0.004	0.033	-0.009			
	(0.050)	(0.042)	(0.035)			
Angels	0.061	-0.128	-0.055			
	(0.112)	(0.094)	(0.078)			
GVC	-0.080	-0.084	0.030			
	(0.171)	(0.142)	(0.118)			
After ODA X Drug	-0.114***	0.173***	0.040	-0.140***	0.158***	0.010
	(0.039)	(0.032)	(0.027)	(0.045)	(0.038)	(0.032)
Category FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Investor FE	NO	NO	NO	YES	YES	YES
Observations	4,475	4,475	4,475	4,475	4,475	4,475
R^2	0.369	0.270	0.187	0.328	0.350	0.297

Adjusted R^2	0.365	0.266	0.182	0.142	0.170	0.103
Residual Std. Error	0.466 (df = 4446)	0.387 (df = 4446)	0.323 (df = 4446)	0.439 (df = 3506)	0.367 (df = 3506)	0.316 (df = 3506)
Note:						*p **p ***p<0.01