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Essays in Applied Microeconomics

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Essays in Applied Microeconomics

by

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Table of Contents

List of Figures

List of Tables

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ABSTRACT OF THE DISSERTATION

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Professor Barton H.Hamilton, Chair

The first chapter of this dissertation quantifies to what extent business accelerators can reduce the venture market frictions for early-stage startups. With a novel non-transferable utility two-sided matching framework, this study shows that business accelerators can close the gaps due to entrepreneurs' gender and experience, but not so much for the differences due to locations. The second chapter studies the relative importance of screening compared to training in the total value creation by business accelerators from the perspectives of market participants. The estimates suggest that the value created by screening, which reflects through the improvement of financing in short-term after graduation, represents less than 1/6 of the total value created by business accelerators. Further, such ratios are especially low for top programs like Y Combinator and TechStars. The third chapter investigates the effects of auditor office location on the client and auditor surplus. Using a two-sided matching market model, we find that, while both clients and auditors bear the costs of geographic distance, auditors disproportionately bear costs. Although distance exerts costs on clients, clients incur distance costs to gain auditor expertise.

Chapter 1

Can Business Accelerators Level the Playing Field for Startups

The unequal access to venture financing and business expertise increases inequality and hinders innovation. This paper examines whether and to what extent a business accelerator can level the playing field for entrepreneurs. With a novel dataset covering the universe of U.S. accelerators from 2008 to 2011, I estimate the value created by accelerators for different groups of entrepreneurs by exploiting preferences revealed during the admission process of for-profit accelerators. I develop a two-sided matching framework to control for sorting and selection. I find accelerators, to a certain extent, can level the difference between startup values due to the founder's experience and gender but cannot offset the advantage of founding a startup in Silicon Valley. Through counterfactual analysis, I find external financial supports of equity-free accelerators have limited ability to assist entrepreneurs who face high difficulty to join accelerators. I do find, however, that direct capital injection to accelerator graduates can improve the admission rates of inexperienced entrepreneurs.

1.1 Introduction

Beginning with the work of Schumpeter [137], economists have viewed entrepreneurs as a primary engine of economic growth. Entrepreneurs innovate through the formation and development of startups, which are key drivers of productivity.[1] However, despite their importance to the economy, entrepreneurs face a variety of market frictions, and many promising startups fail due to challenges in acquiring venture financing or inadequate human capital.[2] Recent research has highlighted the fact that these challenges may be particularly acute for female entrepreneurs, first-time founders, and founders not present in "startup hubs" like Silicon Valley.[3] It is inefficient for the economy to have growth opportunities for startups depend on a founder's demographic characteristics instead of the startup's viability (Hsieh et al. [92]). Consequently, the economic growth generated by startups may be distributed unequally across geographic regions and entrepreneurial success may vary substantially across groups. Addressing market frictions, business accelerators ("accelerator" hereafter), such as the Y Combinator, emerged in 2005 with the assistance of venture financing and business training.[4] Just one decade later, these accelerators have become an important player in entrepreneurship: about one-third of early-stage venture funding went to accelerator-backed startups.[5] With capacity constraints, accelerators admit the best applicants, and prior literature (e.g., Gonzales-Uribe and Leatherbee [81], Yu [151]) has demonstrated that accelerators make these "good" startups better.[6] However, we have limited knowledge on whether and to

[1]See Acs and Audretsch [2] for the role of startups in innovation and Acemoglu [1] for the importance of innovation to economic growth.

[2]See e.g. Amit et al. [8] and Lerner and Schoar [107] for the difficulties entrepreneurs face in acquiring financing. Hsu [93] and Gompers et al. [80] discuss the human capital issues faced by many startups.

[3]See Dutt and Kaplan [56] for a discussion of female entrepreneurs, Gompers et al. [80] on the advantage of experienced founders, and Glaeser et al. [78] for the location effects on startups.

[4]The accelerator is defined as a structured program offering fixed-term and cohort-based training, which include mentorship, and other educational components to participants in exchange for a small share of equity, typically 5%. Section 2 provides more details.

[5]Source: https://pitchbook.com/news/articles/one-third-of-us-startups-that-raised-a-series-a-in-2015-went-through-an-accelerator

[6]The average acceptance rate is below 5% in the US.

what extent the accelerator can assist entrepreneurs who face acute market frictions.[7]

In response, I estimate the value created by accelerators for different groups of entrepreneurs (such as those facing market frictions) by exploiting preferences revealed during the admission process of for-profit accelerators. Under rational expectations, the choice of profit-maximizing agents builds on the expected startup values at graduation[8]. Without accelerators, startups founded by female entrepreneurs, first-time founders, or entrepreneurs not present in startup hubs tend to have a lower valuation. However, the preference exhibited by accelerators may not depend on these demographic characteristics if the accelerators can alleviate the challenges for these entrepreneurs. Due to sorting and interdependence between market participants' choice sets, traditional discrete choice models, like probit or logit, are biased when applied to the accelerator admission process, which is a market with two-sided selections. Because the accelerators set the amount of equity and seed to each startup before the admission starts, this market is a non-transferable utility (NTU) two-sided matching game (Roth and Sotomayor [135]), which excludes negotiation on utility transfers between matched agents (similar to the school-student and patient-doctor matching). I propose a framework to identify the market participants' preferences by comparing actual startup-accelerator matches with other potential but not realized matches. My approach accounts for the endogenous matching process explicitly; thus, it can be used for causal inference.

Compared to transferable utility (TU) matching models (e.g., Choo and Siow [37]), the NTU approach is less restrictive because any matching that can be rationalized by some profile of preferences under TU can also be rationalized by some NTU stable matching (Chiappori and Salanié [35]). Without data on all applicants and potential applicants, existing NTU matching estimators (e.g., Boyd et al. [27], Agarwal [3]) do not work well because

[7] A few papers (e.g.Dutt and Kaplan [56]) have qualitatively studied the accelerator's impact on female entrepreneurs. While also connected to the topic of gender, this paper conducts a quantitative approach to a broader group of entrepreneurs' demographic characteristics (gender, experience, and location).

[8] Without assumption on profit-maximizing agents with rational expectation, the matching model still works, but the interpretation for results may change. I check the validity of this assumption in Section 1.7.

they require information on all market participants to generate consistent estimation.[9][10] My approach builds on a pairwise comparison mechanism (Fox [64, 66]) and examines the relative ranking of a pair of choices, which are independent of other alternatives. I use a maximum score estimator (Fox [66], Manski [111, 112]), which imposes a weaker assumption on unobserved quality and allows for the presence of multiple equilibria.

Due to challenges in data and methodology, much of the existing literature evaluates the treatment effects of a single or a homogeneous group of accelerators by comparing the startups that completed accelerators to those that did not (e.g., Hallen et al. [87], Gonzales-Uribe and Leatherbee [81], Yu [151], Winston-Smith and Hannigan [149]). With a novel dataset covering the universe of the U.S. for-profit accelerators and their participants from 2008 to 2011, I examine the heterogeneity of accelerator value creation by recovering the agents' utility functions for each potential accelerator-startup match.[11] I form these match utilities based on the observable features of the accelerator (e.g., accelerator tiers[12] and cohort sizes), the startup (e.g., business age and founder characteristics), and macroeconomic conditions (financial crisis). Under the assumption of risk-neutral agents, the recovered match utility represents the expected startup value at graduation, which is above $1.5m on average.[13][14]

[9]Even if the researcher has information on all potential applicants for all accelerators, the market size is too big for tractable computation.

[10]Menzel [114] proposes a method to estimate a random sample of a large market. Sørensen [139] imposes strong assumptions on market size.

[11]While data on non-participants is useful for comparing the accelerator value creation with outside options, it does not contribute to this research question.

[12]To control for accelerator quality differences, I include fixed effects for three tiers of accelerators. Tier 1 consists of the two "superstars" (Y Combinator and TechStars), Tier 2 includes other well-known accelerators, and the remaining accelerators are in Tier 3. Although the categorizing rule is endogenous based on ex-post performances, I do not impose quality ranking based on the tiers in estimation. Further details are in the data section.

[13]Without risk-neutral agents, the magnitudes of the estimates have different interpretations than what is presented here. However, the results are still informative to understand the relative importance of various factors in the utility function.

[14]The figure is close to $2m for Tier 1 graduates and lower at $1.2m for Tier 3. Note that the calculated value ignores the unobserved quality and is therefore likely to be downward biased due to selection. Further, because of sorting, this bias tends to be larger in better accelerators.

I find female-led startups have similar valuations compared to their male counterparts in most accelerators, but women suffer a gender difference worth about a half million dollars in the top accelerators, Y Combinator and Techstars. On the other hand, the lack of prior startup-founding experience costs first-time founders about \$300k in an average accelerator, but such a disadvantage disappears in high-quality (Tier 1 and 2) accelerators. Finally, I find startups from startup hubs have an advantage worth about \$110k in the accelerator market.

With the recovered model primitives, I evaluate potential financial support to entrepreneurs with disadvantages in accelerators. Institutions and philanthropic funds have shown a growing interest in supporting accelerators (GALI [73]), and many of the institution-backed accelerators offer free programs to startups by taking no equity. However, the impact of this support is hard to predict in the NTU market due to two countervailing forces. Directly, the support increases the value of the startup which receives the assistance. Indirectly, the support changes the market equilibrium and forces some agents to pick their inferior choices. I find that offering equity-free accelerators to female entrepreneurs, first-time founders, or accelerators outside startup hubs does not increase the admission rates of entrepreneurs who face higher difficulty to join accelerators. The average value increase for the startups founded by these entrepreneurs is also lower than the subsidy size. However, I find providing a USD 150,000 capital injection, which is widespread in the top accelerators nowadays but rare in the others, to accelerator graduates established by first-time founders can increase the admission rates of inexperienced entrepreneurs by 3.5% and female entrepreneurs by 7.1%.

The remainder of this paper is structured as follows. Section 2.2 provides institutional details of the accelerator market. Section 2.4 describes the data and basic summary statistics. Section 1.4 motivates and presents the two-sided matching model and associated maximum score estimator. Section 2.5 discusses the main results. Section 1.6 presents the counterfactual analysis results for the two types of policy interventions. Section 1.7 examines the variations among startup performance after graduation. This section provides a validity check on the assumption that the revealed preference reflects accelerator's ability to assist entrepreneurs with higher difficulties. Section 2.6 concludes.

1.2 Institutional Details

1.2.1 What is an Accelerator

Business accelerators are sometimes called "seed accelerators" or "startup accelerator". I identify individual accelerator programs mainly from Seed-DB (www.seed-db.com), which is one of the best known and most significant public repositories of accelerator programs. Seed-DB defines accelerator as a program that satisfies the following criteria: 1) has an open application process; 2) invests in companies, typically in exchange for equity, at the pre-seed or seed stage; 3) holds cohorts or "classes" of startups, not an on-demand resource; 4) provides a program of support for the cohorts, including events and company mentoring; 5) focuses on teams, and not individual mentoring. The Seed-DB definition covers very similar programs as those under an alternative definition proposed by Cohen and Hochberg [39].[15]

Accelerators target early stage startups but not nascent ones. They are not intended for businesses worth more than tens of million dollars nor nascent entrepreneurs who do not have a solid product or idea yet. Following the early programs, many accelerators invest a small amount of seed money in exchange for equity. But unlike traditional venture capitalists, who confidentially negotiate with entrepreneurs, accelerators announce their offerings to the public and entrepreneurs can easily find such information online.

As shown in Figure 1.1, the whole procedure of accelerators starts with a public announcement of the details and terms of the program, including information on application

[15] Cohen and Hochberg [39] define accelerators as "a fixed-term, cohort-based program, including mentorship and educational components, that culminates in a public pitch event or demo-day".

requirements, resources provided, seed investment, equity share, class size, location, and schedule. Once announced, these terms are not subject to negotiation. Startups submit their applications to accelerators. The admission process is competitive. Applicants to popular programs see the acceptance rate of 1% to 2%, and the average number is around 4% for the U.S. market.[16] Admitted entrepreneurs start the program together at the same time and in the same location. The program lasts for a fixed period, often three months, during which accelerators offer mentorship, network opportunities, and other business support. At the end of the program, accelerators hold a "Demo Day" in which each startup pitches to a group of potential investors. After graduation, firms are officially off the hook in terms of participating in the accelerator, but they can, and often do, become involved in the alumni community.

Y Combinator launched the world's first accelerator in 2005, followed by TechStars in 2006. Both have evolved over the years—Y Combinator started in Cambridge, MA then also in Mountain View, CA. In 2009, it consolidated into a single entity in Silicon Valley with a bigger cohort size. TechStars used a different approach. It has grown to 40 different programs worldwide as of April 2018, since its first launching in Boulder, Colorado. Yet still, they both remain as the very best accelerators. As summarized by Hathaway, the growth in U.S.-based accelerators took off after 2008.[17] The number reached 170 programs in 2014 and held mostly steady afterward. Accelerators have attracted much attention thanks to their outstanding performance. Pitchbook.com reported that about one-third of Series A venture funding went to accelerator-backed startups in 2015.[18] Consistent with my back-of-envelope calculation, participating in some form of an accelerator becomes a check-box on the to-do

[16]Source: https://techcrunch.com/2014/04/20/who-gets-into-accelerators-persistent-men-with-saas-apps-says-study/

[17]Source: http://www.ianhathaway.org/blog/2016/3/1/startup-accelerators

[18]Source: https://pitchbook.com/news/articles/one-third-of-us-startups-that-raised-a-series-a-in-2015-went-through-an-accelerator

list for startups.[19][20]

1.2.2 Accelerator Value Creation

Prior literature (e.g., Yu [151], Winston-Smith and Hannigan [149]) has demonstrated that accelerators create positive treatment effects to early-stage startups with assistance on obtaining venture financing and business training.

Venture financing is an essential source for startups to accumulate physical assets (see Da Rin et al. [45] for a survey). Unlike the investment from venture capitalists, the amount of seed money from accelerators is small and often considered as a stipend for the founders during the program (Hallen et al. [87]). Instead, the accelerator serves as intermediary connecting startups and investors in the venture market. Specifically, accelerators reduce the information asymmetry in the market. With the cohort structure, accelerators have a cost advantage to apply thorough screening (Ramakrishnan and Thakor [131]). By taking small equity with seed investment, they send credible signals to outside investors (Breadley et al. [28]). In addition, many accelerators offer education to improve entrepreneurs' pitching skills and help them to network with potential investors.

Human capital, defined more generally as "managerial capital," is also critical for firm performance (e.g., Bloom and van Reenen [25]). The accelerator offers a platform to facilitate knowledge and resource sharing from experienced mentors/investors with startups. With economies of scale, this mechanism lowers the cost of gathering experienced mentors, offering networking events, and providing valuable business supports. Further, creating a community

[19] Each year there are about 400,000 new firms registered in the U.S. Around 10% of them, or 40,000, are medium to high tech startups (based on Kauffman Firm Survey). According to F6S.com (one of the biggest accelerator program network), the average acceptance rate of accelerators is about 4% in the U.S.. While successful applicants applied 3.3 times before admitted, unsuccessful startups applied 1.8 times. To be conservative, assume each accelerator takes 20 startups per year (GUST 2015 reported 2,968 startups graduated from 111 accelerators in the U.S.), 170 accelerators across the country would receive applications from 30,000 unique startups per year.

[20] Source: https://alexiskold.net/2014/08/19/top-10-reasons-to-join-and-not-to-join-an-accelerator/

of people who share similar interests in the entrepreneurship world, the accelerator can generate a long-lasting impact on its graduates.

In an efficient market, we would like to focus the financing and business training to founders with the best idea and inner ability. However, due to market frictions on information and access to knowledge, we do not know the underlying distribution of startup quality, and therefore provide the limited resource to those we think are good based on prior experiences. Notably, an essential part of the investment decision builds on the startup founders' demographic characteristics, causing acute market frictions for female entrepreneurs (Dutt and Kaplan [56]), first-time entrepreneurs (Gompers et al. [80]), and founder not in startup hubs (i.e., CA, MA or NY) (Glaeser et al. [78]). While evidence suggests that accelerators speed up the growth of high-quality startups, it is unclear whether those startups would be able to grow without accelerators. Specifically, we have scant knowledge on whether accelerators can assist startups with potential but may be ignored by traditional investors due to the founders' demographic characteristics.

Notwithstanding the limited understanding of accelerators, there is a growing interest in using accelerators to assist entrepreneurs who face high difficulties. According to the 2016 report by Global Accelerator Learning Initiative (GALI [73]), which covers more than 164 accelerator programs globally, about 40% of the accelerators received philanthropic funding in 2015, and over 19% relied on philanthropy for at least half of their total funding. Very few programs (7%) generated revenue from equity returns.

1.2.3 Value Determinants of Accelerator Admission Decisions

Without an established business, the early-stage startup quality largely depends on its founding teams' ability to generate and execute high-quality ideas (Stross [141]).[21] Because in-

[21] Labor literature often includes the education level to capture human capital differences. In my dataset, over 99% of entrepreneurs are college graduates. According to Y Combinator (Stross [141]), the only information on education concerns whether the entrepreneur entered a college. I tested model controlling for

vestors do not observe an entrepreneur's ability, they make investment decisions partly based on their prior knowledge/experience of founders with similar demographic characteristics, raising a specific challenge for people who are not traditional entrepreneurs or who are associated with low-quality firms due to historical reasons. One example is the female entrepreneurs, who are known to have disadvantages in raising venture financing (e.g., Kanze et al. [98], Eddleston et al. [59]). To examine whether women still have disadvantages in accelerators, I study the impact of "Female Founder" - an indicator of whether at least one founder in the team is female in the accelerator admission market.[22]

First-time founders, who lack business knowledge, also face a greater challenge of attracting traditional investors as opposed to serial entrepreneurs (e.g., Hsu [93], Gompers et al. [80]). While prior literature (e.g., Hallen et al. [87], Gonzales-Uribe and Leatherbee [81]) demonstrates that the accelerator creates a positive treatment effect for both experienced and inexperienced entrepreneurs, it is unclear whether accelerators prefer serial entrepreneurs. To capture this, I control the "Inexperienced Founder" - an indicator of whether no members of the founding team have prior entrepreneurship experience.

Besides, founder's general work experience, as may be captured by the entrepreneur's age, is a signal for startup quality too. In contrast to the majority of entrepreneurs in the U.S. start their business around their forty-year-old (Azoulay et al. [12]), the average founder age in my sample is less than thirty, especially in the top programs. Hincapié [89] argues one reason for the late entry into entrepreneurship is the uncertainty of own ability, which can be mitigated by experience accumulation. From this perspective, the accelerators may create more value for younger participants by providing feedback (Yu [151]). I explore this feature by studying the effect of average age of the startup founding team.

Community support is essential for startup growth (e.g., Glaeser et al. [78], Audretsch and

whether the founder has a graduate degree and found the education impact is close to zero.

[22] One could argue it would be better to study firms with female founders only. Unfortunately, I have limited observations with a founding team of all women.

Lehmann [11]). While many local governments provide generous assistance to promote entrepreneurship, we still find the majority of successful startups comes from startup hubs like Silicon Valley. A potential reason is that firms founded in startup hubs have better networks to help with obtaining talent and support (Kenney [99]). I examine whether accelerators can substitute this disadvantage for firms established outside startup hubs by studying the "Founded Outside Startup Hubs" - an indicator of the startup founding location. In this paper, I define the startup hubs to be MA, CA or NY.

The cohort-based structure is an essential feature of accelerators. While the economies of scale can help accelerators to pool resources and increase profitability, larger class size is not necessarily beneficial for individual startups. While it can create more prominent peer and network effects, large class size reduces the effectiveness of education (Angrist and Lavy [9]). I include a "log cohort size" to capture the value variation in this perspective. I also include fixed effects of each accelerator tiers to capture additional quality differences. Further, the investment of the Start Fund (see appendix for details) to every Y Combinator graduates in 2011 improves the accelerator's value with direct capital injection. I capture its effect with an indicator of such events.

Macroeconomic conditions, especially the venture investment environment, can affect accelerator value creation. I control this external effect with an indicator called "One Year After Crisis". This indicator equals to one if the accelerator program happens before July 2010, which is one year after the official end of the great recession of NBER definition. I use this time point because 1) According to PitchBook, while venture investment deals came back to the upward trend in 2009, the recovery only speeded up since the third quarter of 2010, especially for the market of early startups which are targeted by "Angel/Seed" and "Early VC". 2) The accelerator applications and admissions were decided at least several months ahead of the actual program. Graduates from 2009 programs were unlikely to be sure of when the financing condition would improve during their applications.

1.3 Data

1.3.1 Data Sources

I construct a novel dataset covering U.S. accelerators that existed from 2008 to 2011.[23] I study this time frame because the majority of currently well-known accelerators emerged during this period, and it allows me to collect ex-post startup performance up to five years. To have all accelerators maximize financial return, I exclude accelerators with different utility functions, such as those with restrictions on the community they serve and those that do not take any equity. The exclusions are unlikely to cause a significant impact as they only represent about 2% of the data. I also dropped startups with missing information on founder characteristics. Hereafter, I define a "program" as a cohort of accelerators. Some accelerators run multiple programs in various locations across years. In total, I identified 74 programs, representing 27 accelerators and 776 startup graduates.

I use CrunchBase, AngelList, CapitalIQ, CBinsights, VentureXpert, and Linkedin to get the details of each program and its participants. Data on private firms often lack crucial information and may suffer a self-reporting bias since successful startups are more likely to release information to the public. To mitigate such concern, I cross check each firm by searching for related news and press releases. The bias of self-reporting is mild in this paper because I have found information even for failed startups, thanks to the publicity and popularity of accelerators.

Data on non-participants of accelerators is helpful to understand the value added by accelerators relative to other options. However, it is not necessary for this paper to generate consistent estimates (details in the model section). Since my focus is on whether founders' demographic characteristics affect their admission in accelerators, the non-participants data

[23] I collected data from 2005, the founding year of the first accelerator. I restricted attention to observations after 2008 as there were only two programs (Y Combinator and TechStars Boulder) before 2008.

does not contribute to my research question either.

To characterize accelerators, I collect information on their location, size, and terms offered (amount of seed investment and equity share). For each startup, I obtain its business age, location, founders' background (gender, education, and entrepreneurship experience), and operation (acquired, dead or operating) and financing status.

To further capture some unobserved differences among accelerators, I categorize accelerators into three tiers and control the fixed effects of each. The first tier includes the two widely acknowledged "superstars" in this market - Y Combinator and TechStars. The second tier consists of all the accelerators who received ranks from the "Seed Accelerator Ranking Project" (SARP) except for the two in the first tier.[24] All the rest of the accelerators are in the third tier. While all Tier 1 and Tier 2 accelerators are still running, six of the Tier 3 accelerators stopped or joined other accelerators as a chapter. Note that I do not impose any restriction on the quality ranking across tiers and the model estimates do not depend on the endogenously generated categorizing rule of tiers.

1.3.2 Summary Statistics

Table 1.1 shows a summary of programs and startups across accelerator tiers.

The accelerator participants are early-stage startups - mostly firms before any venture capital financing. Better accelerators, as indicated by the tiers, tend to take lower equity and

[24]SARP is led by Yael Hochberg and probably the only ranking conducted by economics researchers. Although the exact ranking criteria are unknown to the public, according to the website, "*The goal of our project is to provide greater transparency regarding the relative performance of programs along multiple dimensions that may be of importance to entrepreneurs. Many of the metrics in question, such as fundraising and valuations, are metrics accelerators and startups are reluctant to publicize out of concern for negative competitive effects should they become widely known to investors and competitors. As an independent, non-partisan research entity run by academics, we collect this sensitive data in confidence, distill it down, and provide information on the relative success of the programs and of the phenomenon as a whole – without revealing individual deal details. Our rankings are meant to provide guidance for entrepreneurs who are considering going through an accelerator, and who are wondering how they differ on performance across various categories.*" SARP has been running since 2013, and the ranking is available since 2015. See: seedranking.comcom

have bigger classes. A potential reason is that better programs have a lower cost of pulling resources to sponsor larger programs and create a higher total return. Additionally, Tier 1 accelerators take lower equities from startups but do not give the highest seed investment. The second tier programs are the most generous ones regarding startup valuation (calculated as seed/equity).

In my dataset, about 37% of the accelerator programs are found in startup hubs (CA, MA, NY). This pattern is similar to the geographic distribution of accelerators in 2015, in which about 40% of all accelerators in the U.S. located in the well-known technology startup hubs and major cities of San Francisco-Silicon Valley, Boston-Cambridge, and New York.

The accelerator participants are significantly younger than non-participants. Azoulay et al. [12]reported that the average age of startup founders in the U.S. is 41.9. High-tech founders are a bit younger but still around 39 to 40, and this age range is not very different in startup hubs. If we interpret age as a proxy of general work experience, this indicates that accelerators' assistance may be a substitute for human capital accumulation over time. Further, while some consider accelerators are designed for first-time entrepreneurs[25], I find one-third of accelerator participants have founded some company before. While not reported in the table, over 99% of entrepreneurs in my data have college degrees. About 35% of them also have graduate degrees, close to the figure of comparable non-participants during the same period (see appendix). The female participation rate, which is at 10% on average and below 5% in Tier1, is low because 8%~16% of startups, which received first venture funding during the same period, are founded by women.[26]

Most early accelerators focus on high-tech startups, especially in the IT related fields, aiming to generate a higher return and social impact. While high-tech is still a focus, new accelerators have recently diverged to work with different industries and communities. Despite

[25]Source: https://alexiskold.net/2014/08/19/top-10-reasons-to-join-and-not-to-join-an-accelerator/

[26]Source: https://techcrunch.com/2018/01/15/the-portion-of-vc-backed-startups-founded-by-women-stays-stubbornly-stagnant/

heterogeneity in concentration and purpose, the majority of accelerators follow the framework of Y Combinator and TechStars. As of 2016, Y Combinator had invested in about 940 companies, including some well-known unicorns such as Dropbox and Airbnb.[27] Y Combinator has a combined market capitalization of over $65b. About 170 Y Combinator graduate startups have been acquired with the estimated total value of over $3b. However, not all accelerators have matched Y Combinator's success. For example, neither South Carolina's NextStart nor Minnesota's Project Skyway lasted for more than two years. While NextStart closed quietly, Project Skyway turned into the Skyway Fund and started traditional angel investing after its second cohorts finished in 2012.

The first two rows of Table 1.2 show the five-year in operation rates, which is the percentage of graduates that are still in operation and have not yet been acquired, and the five-year exit rates, which is the percentage of graduates that have been acquired. Financing performance, including portions of startups which obtained venture financing within one year, five years, and 2nd-5th year after graduation, are reported in the last three rows. Tier 1 accelerators dominate in all the performance measures reported. Compared to those from Tier 3, graduates from Tier 2 accelerators enjoy better venture financing.

1.3.3 Reduced-form Evidence

Assuming accelerators are the only decision-makers in the admission market, one can use a probit model to study the revealed preference of accelerators.[28] Specifically, I form all potential matches between accelerators and startups and construct the dependent variable as the indicator of whether the match is observed in data. Table 1.3 reports the estimation results.

The findings indicate assortative patterns such that relocation is costly and Tier 1 creates

[27] Dropbox is the first public firm which graduated from an accelerator as of April 2018.

[28] The alternative approach, which studies the preference of startups when the entrepreneurs are the decision makers, is irrelevant to the research question.

higher value for inexperienced entrepreneurs. The results also suggest that accelerators prefer startups with experienced founders outside of startup hubs, while the entrepreneur gender has no significant impact. The prediction power of this model is low, at around 27%.

Table 1.4 shows the OLS estimates for the ex-post performance of accelerator graduates. While Tier 1 and 2 graduates see better financing after graduation, the heterogeneity only exists within one-year after graduation (the short run). Older startups tend to live longer and have a higher chance of obtaining funding in the short term. The experience, age, and gender of entrepreneurs have no significant correlations with the startup ex-post performance. I do not find that startups from startup hubs associate with higher value creation.

The preference of for-profit accelerators depends on the expected startup performance after graduation. From this perspective, the two table results conflict with each other in several dimensions. For example, Table 1.3 indicates the startup age has no significant correlation with firm value at graduation while Table 1.4 suggests it positively associates with the ex-post performance.

While the OLS findings are inconclusive due to the concern of endogenous sorting, the probit results are also biased by abstracting away from the market competition. The probit model assumes the admitted startups are the accelerator's most preferred candidates, but in reality, many accelerators admit sub-optimal choices because their most preferred startups joined other accelerators. The following section proposes a two-sided matching model to address this issue.

1.4 A Two-Sided Matching Model

1.4.1 Why Use a Matching Model

The accelerator admission is a match between the accelerator and startups. It is instructive to observe that each startup deliberates among many viable alternative accelerators, and each accelerator considers viable startups from their pool of applicants. Through the equilibrium channel, the values of possible alternative matches—both implicit and explicit applications—provide a bound for the value of each realized match. Formalizing this intuition, this paper analyzes the market participants' utility function with a revealed preference approach. I use the characteristics of each startup and accelerator's alternative matches to estimate the value of the matches that do occur.

Competition exists on both sides of the accelerator market. Because accelerators have limited capacity, they only admit the best startups. At the same time, accelerators compete to attract the good (desirable) candidates because each startup can only join one accelerator. By assuming that each agent's decision is independent and has no externalities, standard discrete choice models, such as logit and probit, cannot accommodate markets with two-sided selection and competition in the choice set (See Mindruta et al. [116] for a detailed discussion). To address this challenge, economists have developed two-sided matching models to capture this market structure explicitly.

I model the accelerator admission as a two-sided matching game (Roth and Sotomayor [135]). Each accelerator-startup match creates a joint match value and the match value is split according to the pre-announced equity-share and seed investment, which are considered exogenous in this paper.[29] Agents from both sides of the market maximize payoffs by choosing matches with agents on the other side.[30] In equilibrium, agents have no feasible deviations to match with other partners and weakly increase the payoffs for all participants. In the estimation, I construct counterfactual matches to each pair of observed matches within the same market by switching their partners. Comparing pairs of observed matches with their counterfactual matches yields sets of inequalities required by the equilibrium condition.

[29] This is based on the fact that such terms are fixed once the accelerators announce them.

[30] To guarantee the existence of equilibrium, this paper abstract away from potential gain from complementarity in the accelerator portfolio. It is difficult for the accelerator to make decisions based on the portfolio given a large number of applications. In reality, it is not rare to see two direct competitors in the same cohort (Stross [141]).

Given these inequalities and a parametric form for the match value function, I choose the parameter vector that maximizes the fraction of inequality sets that hold. This is the maximum score estimator I propose in this paper. Compared with similar estimators as in Fox [66] and Akkus et al. [6], this estimator studies non-transferable utility matching games, in which neither the uniqueness or the competitiveness (efficiency) of equilibrium is guaranteed.

1.4.2 Non-Transferable Utility Two-Sided Matching Model

The most common, and arguably the most important, criteria to separate different types of matching model is between TU and NTU utility models (Chiappori and Salanié [35]). Under TU matching games, matched agents endogenously decide their internal transfer from one side to the other. An example is the CEO-company matching in which agents of both sides negotiate terms of the compensation package. For other markets, such as student-school matching, transfers are simply excluded, and NTU framework would make more sense rather than TU models. The NTU model fits the accelerator market because all equity-share and seed amount are not subject to negotiation between agents, similar to the school-student and patient-doctor matchings. Further, Chiappori and Salanié [35] point out that TU matching is more restrictive than NTU matching. In fact, any matching that is rationalizable by some profile of preferences under TU is also rationalizable by some NTU stable matching.

Compared to TU matching, the number of empirical researches on NTU is much smaller (Graham [82]). The challenges mainly come from two features of NTU matching models. First, there exist multiple equilibria without strict model assumptions, and second, the NTU pairwise stable condition, which will be explained in details later, indicates that four possible underlying mechanisms can generate the same matching pattern. The latter raises a significant concern for many empirical models as researchers often only have access to matched data in practice. Prior literature makes various simplifying assumptions. Boyd et al. [27] rule out multiplicity and the underlying match-forming mechanism by assuming the status quo assignment is the product of the Gale and Shapley [72] deferred acceptance algorithm (with firms proposing). Sørensen [139] imposes a fixed utility sharing rule for all possible matches in the market to guarantee a unique equilibrium. He gets rid of the second challenge by restricting positive correlation between first stage matching value and second stage ex-post performance of such matching. Agarwal [3] restricts one side of the market as having a homogeneous preference to the other side to guarantee a unique equilibrium. His sign restriction and assumption of covariates with conditional full support address the second challenge of identification.

Matching models can also be categorized by the capacity size of each agent on both sides of the market. If one agent can only match with at most one partner, it is one-to-one matching; if agents on one side can match with multiple agents on the other side, it is many-to-one matching; it is many-to-many matching if both sides can partner with multiple agents. The accelerator admission market fits into the two-sided many-to-one NTU matching framework.

In this paper, I propose a maximum score estimator for the two-sided NTU matching model. I show that the total match value is identified with only data on matched pairs if there is enough variation in the sharing rule and there exists some non-trivial (with the parameter not equal to zero) covariate with full support. This approach has several advantages: 1) it does not suffer the curse of dimensionality, 2) it is consistent with an endogenous dataset, and 3) it allows for the existence of multiple equilibria.

1.4.3 Model Setup and Functional Form

During the accelerator admission process, I assume agents on both sides of the market share a total match surplus U_{as} for a given match between the accelerator a and the entrepreneur s. Denote the match between a and s as (a, s). Let U_{as}^a be the payoff for a from match (a, s) and U_{as}^s be the payoff for s from match (a, s). Agents in the market maximize their expected payoffs, which can be written in the following forms:

$$U_{as}^{s} = (1 - E_a) * U_{as} + \beta_t t_a$$

$$U_{as}^{a} = E_a * U_{as} - \beta_t t_a$$

where E_a is the equity share of the accelerator a and t_a is the seed investment from the accelerator a. Both E_a and t_a are exogenous. β_t is a parameter capture the relative importance of the seed investment. By separating t_a from U_{as}, I assume the seed investment as a stipend for entrepreneurs, which does not increase the firm value. This assumption is not important for the model identification and can be changed.[31]

Under additional assumptions that the for-profit accelerators and entrepreneurs make decisions based on the expected financial return of startups and all agents are risk neutral, the total match surplus can be interpreted as the expected startup value at graduation. This interpretation does not necessarily exclude non-firm related utilities such as access to the accelerator network or having a high-quality entrepreneur as a mentor in the future. The key assumption here is the utility is divided according to the equity share. Because the model relies on agent's choices to infer the accelerator value creation, this approach recovers the value created from the standpoints of the startup founder and the accelerator holder.[32]

Let the observed covariates of entrepreneur be X_s, accelerator covariates be X_a, and their

[31] Here I abstract away from potential individual costs on both sides of the market. The individual costs do not affect the estimation if the startup (accelerator) faces the same individual costs for all possible accelerators (startups). Startup's individual cost includes the founders' time and living expenses during the accelerator program. It may also include migration spendings if the startup needs to relocate. Since the majority of accelerator programs last for three months, the cost variation on time spending is small. Due to data limitation, I assume the living costs are very similar across accelerators. The migration cost includes the firm's moving expenses and potential business loss. This cost can directly reduce the firm valuation and is therefore controlled by a relocation dummy in U_{as}. I assume the accelerators face the same cost across all possible startup candidates.

[32] The model identification allows agents from each side of the market to have separate utility functions as in the case of Agarwal [3]. I impose the current approach because 1) with fewer parameters to recover, this model has lower requirements on data; 2) although it has a stronger assumption, this model fits the accelerator market features.

interactions be X_{as}. Let $X^{as} = \{X_s, X_a, X_{as}\}$. I assume a quasi-linear functional form for U_{as}

$$U_{as} = X^{as}\beta_x + \varepsilon^{as}$$

where $X^{as}\beta_x$ captures the deterministic part of the match value and ε^{as} is the unobserved quality of each potential match. The model primitives are the vector of $\beta = \{\beta_x, \beta_t\}$.

Some additional model assumptions: 1) It is a static model in which all observables are exogenous. 2) Each year is a separate market.[33] Agents on one side of the market can only be matched with agents from the other side of the same market. 3) Some accelerators run multiple programs in various locations across years. I model the matching between programs and startups. 4) Each program can admit multiple startups but each startup can only join one program. 5) All agents have complete information about the market.

1.4.4 Model Identification And Estimation

Assuming the observed matching is an equilibrium, any two pairs of observed matches should satisfy the pairwise stable condition (Roth and Sotomayor [135]). Following previous notations, let a and a' be two different accelerators and s and s' be two different startups. The four agents are in the same market so there are two potential pairs of matches: $\{(a, s)\,(a', s')\}$ and $\{(a, s')\,(a', s)\}$. Let the $\{(a, s)\,(a', s')\}$ be a stable match (observed) then the pairwise stability condition indicates at least one of the following conditions to hold (see appendix for details):

- CONDITION A: $U^{a}_{as} > U^{a}_{as'}$ & $U^{a'}_{a's'} > U^{a'}_{a's}$
- CONDITION B: $U^{a}_{as} > U^{a}_{as'}$ & $U^{s}_{as} > U^{s}_{a's}$
- CONDITION C: $U^{a'}_{a's'} > U^{a'}_{as'}$ & $U^{s'}_{a's'} > U^{s'}_{as'}$

[33] This assumption is made for convenience and does not affect the model result's consistency

- CONDITION D: $U^{s'}_{a's'} > U^{s'}_{as'}$ & $U^{s}_{as} > U^{s}_{a's}$

In estimation, I randomly pick two pairs of matches in the same market each time as an observation, and construct the sample as $\{(a_i, s_i)\,(a'_i, s'_i)\}$, where $i = 1, 2, 3, ..., N$ and N is the sample size.[34] Note that each time the pairwise stable condition depends on the agents' preference over binary choices - whether she should stay with current partner or switch to the alternative partner.

The proposed estimator builds on the so-called rank order property, similar to those in Fox [64, 66]. For any two pairs of observed matches, (a, s) and (a', s'), denote $f_a(a,\, s : \beta) = E_a * X^{as}\beta_x - \beta_t t_a$, so that $U^a_{as} = f_a(a,\, s : \beta) + E_a * \varepsilon^{as}$. Similarly, define $f_s(a,\, s : \beta) = (1 - E_a) * X^{as}\beta_x + \beta_t t_a$. The rank order property says that 1) $f_s(a,\, s : \beta) > f_s(a',\, s : \beta)$ if and only if $Prob(U^s_{as} > U^s_{a's}) > 50\%$, and 2) $f_a(a,\, s : \beta) > f_a(a,\, s' : \beta)$ if and only if $Prob(U^a_{as} > U^a_{as'}) > 50\%$. The intuition is that the deterministic value of a given match agrees with the unobserved value in expectation. A sufficient condition for the rank order property is that ε^{as} follows a distribution consists with the median independence feature as in Manski [111, 112], such that $Median(\varepsilon^{as}|X^{as}) = 0$.

Following a rank order property, the pairwise stability condition can be transformed in to the following maximum score estimator after some simple algebra.

Denote $C_i = \{(a_i, s_i), (a'_i, s'_i)\}$ and $\tilde{C}_i = \{(a'_i, s_i), (a_i, s'_i)\}$ for each possible pairs i. Let $Sta(C_i, \beta) = 1$ if and only if $1[f_a(a,\, s : \beta) - f_a(a,\, s' : \beta) < 0|C_i, \beta]1[f_s(a',\, s' : \beta) - f_s(a,\, s' : \beta) < 0|C_i, \beta] = 0$ and $1[f_a(a',\, s' : \beta) - f_a(a',\, s : \beta) < 0|C_i, \beta]1[f_s(a,\, s : \beta) - f_s(a',\, s : \beta) < 0|C_i, \beta] = 0$; Otherwise, $Sta(C_i, \beta) = 0$. With the intuition that the true β maximize the number of times the deterministic value correctly indicates the pairwise stability as the

[34] Because the sample does not need to be i.i.d., one can pick all possible pairs of matches in the data when the data size is small.

sample gets large, the proposed estimator has the following objective function:

$$\bar{\beta} = argmax_{\beta}\frac{1}{n}\sum_{i=1}^{n}\left(1[Sta(C_i,\beta)=1]-1[Sta(\tilde{C}_i,\beta)=1]\right)$$

The model is unidentified without additional information because all four conditions of the pairwise stability, which represent different underlying preferences respectively, can generate the same matching pattern. Following the intuition in Tamer [143], I show the identification with exclusion restrictions on each side of the market. The intuition is to have one of the four conditions bind for some non-trivial subset of the observed matching. In practice, I use the variations of equity-share and seed, which are exogenous once the admission starts, among different accelerators to identify parameters that relate to one side of the market. For the other side, I use the startup age, which is non-trivial in the value creation and has enough variation conditional on other observables (see appendix for detailed evidence).

Based on the pairwise comparison mechanism, the estimator only requires the relative ranking of the two given choices in each observation. Because the relative ranking does not depend on the existence of other possible choices, the estimator is consistent with non-random samples. This feature is critical when not every agent is matched in the market and researchers only observe matched pairs. Details on the identification and estimator features are provided in the appendix.

1.4.5 Subsampling and Confidence Intervals

I follow Akkus et al. [6] to obtain subsampling and confidence intervals for the maximum score estimator. Normalizing the startup age to have a parameter of $+1$ and -1 respectively, I estimate the matching models by running the differential evolution optimization routine from 40 different starting points (20 each for the positive and negative normalization respectively) and selecting the coefficient vector that yields the highest value for the objective function. For valid inference, I generate the confidence intervals using the subsampling procedure described by Politis and Romano [129] and Delgado et al. [51] to approximate the sampling distribution. I randomly conduct 100 of these subsamples with size at about one third of the total data set. .

For each of the subsamples, I estimate the parameter vector as for the whole dataset. Call the estimate from the sth subsample $\hat{\beta}_s$ and the estimate from the original full sample $\bar{\beta}$. The approximate sampling distribution for the parameter vector can be computed by calculating $\tilde{\beta}_s = (n_s/N)^{1/3}(\hat{\beta}_s - \bar{\beta}) + \bar{\beta}$ for each subsample, where N and n_s are the total sample size and given subsample size respectively. I take the 2.5th percentile and the 97.5th percentile of this empirical sampling distribution to compute 95% confidence intervals for all of the estimates.

1.5 Main Results

Table 1.5 presents the estimates of the match value function. Model 1 includes no interactions between observed factors of the two sides of the market. Model 2 extends Model 1 to study the heterogeneity with interactions. The reported parameters are normalized to +1 of the startup age as it generates the highest score. The positive parameter of startup age indicates that the accelerator cannot fully offset the advantage of older firms, which tend to have lower risks (see Appendix A.2). However, as indicated by the parameter's magnitude, this factor is not very important in the accelerator value creation function.

For a convenient interpretation, I re-normalize the coefficients to the dollar value based on the "Start Fund" parameter, which represents a $150k increase. The rightmost column of Table 1.5 reports the dollar-normalized value. One caveat of this approach is that the Start Fund offer is a convertible debt which is not entirely cost-free to the startups. Therefore, the calculated value is likely to be lower than the agent's actual dollar amount. Alternatively, I can normalize to the seed investment value. However, this approach gives a more biased result because the seed investment does not play an essential role in the accelerator value creation. Nevertheless, the result after normalization based on the Start Fund parameter indicates the seed investment worth $40k on average, close to the average seed investment size.

1.5.1 Preferences For the Entrepreneur's Gender, Experience and Location

Female entrepreneurs face a higher challenge to obtain venture financing even after control for firm quality (Dutt and Kaplan [56]). Model 1 of Table 1.5 reports that women also have disadvantages in the accelerator market. While Model 2 also presents a negative coefficient of for "Female Founder", I find women benefit from the cohort structure as indicated by the positive coefficient of the interaction between the female founder and cohort size. This finding is consistent with the results of Linehan and Scullion [108], which reports that women face difficulties in networking in male–dominated industries such as the venture investment market. Considering that all but one accelerator program have cohorts with at least four startups, the sum of parameters of "log(Cohort Size)*Female Founder" and "Female Founder" is close or above zero, indicating women have no disadvantage in Tier 2 and 3 accelerators. In Tier 1, female-led startups see a substantial disadvantage worth about half a million dollars. One potential explanation is that Tier 1 accelerators discriminate against women. In response to the criticism of admitting very few female entrepreneurs, Paul Graham, co-founder of Y Combinator, points out that they have far fewer female applicants (Stross [141]) although the acceptance odds for women is higher. Another potential explanation is that because women tend to prefer a less competitive environment (Niederle and Vesterlund

[120]), they may gain less in the fast paced program of top accelerators.[35]

Without accelerators, serial entrepreneurs (Hsu [93], Gompers et al. [80]) tend to produce better business and attract more venture investors. In the accelerator market, Model 1 reports that the prior entrepreneurship experience does not matter on average. However, with the decomposition of Model 2, I find this is only true in Tier 1 and 2 accelerators. The similar magnitudes of "Inexperienced Founder", "Tier 1*Inexperienced Founder", and "Tier 2*Inexperienced Founder" point out that the experience with the best accelerators levels the difference between experienced and inexperienced entrepreneurs. The insignificant parameter of founders' age, which is another proxy for entrepreneurs' experience, supports this result by indicating that accelerators are helpful to reduce uncertainty for young entrepreneurs.

Accelerators can promote the local entrepreneurship ecosystem (Fehder and Hochberg [62]) by pooling regional resources to focus on startups with high potential. Model 1 and 2 generate different findings for the startup founding location effect. Because Tier 1 accelerators concentrate in startup hubs, firms founded in startup hubs, which also tend to have higher rates of inexperienced and male entrepreneurs[36], see lower cost to join these accelerators. Therefore, after the decomposition in Model 2, the positive parameter of the indicator of startup founding location flips to negative. The result suggests that accelerators still prefer firms founded in startup hubs, indicating that the pooled resources are not sufficient to replace the better environment in places like Silicon Valley. On the other hand, relocating firms to participate accelerators in startup hubs is not optimal either because such relocation costs are around USD 670,000 (on average).

[35] The top programs are very competitive (https://alexiskold.net/2014/08/19/top-10-reasons-to-join-and-not-to-join-an-accelerator/). Stross [141] points out that the weekly updates with mentors and peers create a high-pressure environment in Y Combinator.

[36] Correlations are 0.017 and 0.057 respectively.

1.5.2 Other Findings

The negative coefficient of log(cohort size) in Table 1.5 indicates that the adverse education effects dominate the positive peer/networking effects for individual firms in a large cohort. Based on this finding, it is not surprising to see that Y Combinator shrank its class size in 2012.[37] With a coefficient of 0.15, slightly lower than 10% of Tier 1 average total match value, the offer of the Start Fund's convertible debt creates value but not a significant amount in relative scale for the Tier 1 programs.

As indicated by the parameter of macroeconomic condition dummy "One-Yr-Aft-Crisis", which equals to one when the general venture investment condition is poor (during the crisis and one year after its official end), the accelerators create higher value when there are fewer outside options. There are two potential reasons: 1) because there are limited alternatives outside, more resources, such as high-quality mentors, contribute to improving the training of accelerators during the crisis; 2) the accelerator improvement in financing becomes more critical because the chance to obtain funding outside is small. After careful research, I do not find any significant resources added, which might improve the accelerator's training, concentrated around the end of the financial crisis. Since accelerators attract applicants through public media channels, such improvement is unlikely to be confidential or only internally announced. Further, I find an increasing trend in the long-term performance across graduates over years, conflicting with the better resource argument.[38]

Assuming financial return maximizing risk-neutral agents, the match value represents the expected startup value at graduation. Table 1.6 shows a summary of the value captured by deterministic parts across accelerators.

On average, the accelerator participants anticipate startups at graduation to be worth more than one and a half million dollars based on my calculation using deterministic factors.

[37]Source: http://seriousstartups.com/2012/12/03/ycombinator-shrinks-class-size-too-smaller/

[38]The 5-year survival rates: 38.96% for 2008, 39.00% for 2009, 37.30% for 2010, and 47.53% for 2011; The 5-year funding rates: 33.77% for 2008, 37.00% for 2009, 44.16% for 2010, and 57.88% for 2011.

Although the actual expected value is likely to be higher because the matched startups tend to have better draw in the unobserved quality, the calculated value is already much higher than the startup's valuations reflected through calculating seed/equity. The finding again supports that the seed investment is not a key component in the accelerator value creation. Pitchbook reported that the median valuation of seed-round startup during the same period is about \$3m to \$4m.[39] Considering that the firms covered in the Pitchbook report are generally one or two years older than the accelerator graduates and about 30% to 40% of accelerator graduates fail, the calculated results are likely to be close to the real value.[40]

The Tier 1 accelerators have significant advantages in value creation, about 15% higher than Tier 2 and 40% higher than Tier 3. The edges are not entirely due to the sorting effect. Instead, the program quality premium, as captured in the Tier 1 dummy, contributes to 13% of Tier 1 value creation.[41]

1.6 Policy Evaluations

The previous findings indicate that the accelerator admission still depends on the entrepreneur's demographic characteristics, although such dependency is lower than that of traditional investors. To address this issue, external financial supports, such as offering equity-free accelerators for certain groups of startups, are popular in the accelerator market.[42] For example, Rockhealth and Portland Seed Fund offer each firm \$20k and \$25k respectively but do not take any equity. However, the effect of financial support is hard to predict due to two countervailing forces. On the one hand, if the market equilibrium stays the same (i.e., no change in the matching), this intervention directly increases the startups' value by an amount equi-

[39]In my dataset, the median size of venture funding within one year after graduation is \$0.78m. Pitchbook Source: https://qz.com/1051121/the-median-value-of-seed-stage-startups-hits-their-highest-valuation-on-record-6-2-million/

[40]See the appendix for a comparable dataset on average age of firms at their first venture financing.

[41]Tier 1 parameter of 0.23 divides the total value of 1.73, which gives 13.34%.

[42]See a list of equity-free accelerators at https://lootstrap.com/equity-free-startup-accelerators.

valent to the support. If only one accelerator receives such support, the value increase of the accelerator's graduate can be higher because the accelerator also attracts better candidates by offering higher value. On the other hand, if such grants award multiple accelerators, a "cannibalization" effect arises. Because of the market competition, the support can generate a new market equilibrium, and indirectly forces some startups to match with their inferior partners (or stay alone). If the increase from the direct effect cannot offset the decrease from the indirect effect, the net benefit of the policy intervention can be negative for the targeted communities.

The examples in Table 1.7 illustrate the impacts of countervailing forces. In both cases, I assume the utility share between accelerators and firms are fixed and remain the same for all participants so that the total match utility determines the matching pattern. In the first case, the subsidies to both accelerators decrease the overall welfare of the market by making one accelerator worse off; in the second case, a subsidy to only one accelerator makes all market participants better off.

In this section, I evaluate the effectiveness of two policy interventions to help constrained entrepreneurs. The first one studies the effect of subsidies to replace equity funding with a grant and the second one examines the impact of additional capital injection to startups (similar to the case of Start Fund for Y Combinator in 2011). For each of the analysis, I impose three types of subsidies. Because female entrepreneurs have lower chance to join Tier 1 accelerators, the first type called "Gender Subsidy" supports female applicants for Tier 1. The second type called "Exp Subsidy" assists first-time founders to increase their opportunity to enter Tier 3. The last type called "T3 Subsidy" aims to help Tier 3 accelerators located outside of startup hubs to boost local economy.

The proposed estimator does not capture the value of agents' outside choices and identifies the model primitives based on necessary (i.e., the pairwise stability) but not sufficient conditions. Although this approach imposes weaker requirements on data during estimation, it causes several challenges to conducting a counterfactual analysis.

First I have limited information on the distribution of unobservable quality of each potential match. For robustness, I simulate the error terms 200 times with a normal distribution with mean zero and standard deviations of 1, 2, 3 and 5, respectively. The general patterns are similar, and therefore I only report the results with the standard deviation of one. Second, I do not have information on which equilibrium is realized in the data. In response, I use the Gale and Shapley [72] algorithm to form matches with startups proposing[43], which is likely to be close to the reality given the low acceptance rate of accelerators.[44] Because it generates the startup-optimal matching (Roth and Sotomayor [135]), this approach is in line with the purpose of the policy interventions to improve the startup growth. Third, I do not have information on the population of all potential applicants of accelerators. Prior literature (e.g. Agarwal [3], Akkus et al. [6]) conducts counterfactual analysis using the original dataset assuming all market participants are observed. However, prohibiting agent's entry and exit, this approach is not very informative in this study given a large number of unobserved accelerator applicants.[45] In response, I evaluate the policy impacts using simulated startups. I simulate 750 firms each year across four years and generate the firm characteristics based on the moments of observed data.[46] Although the simulated dataset is not representative to the population of all accelerator applicants, it can capture the features of those high-quality startups which have higher chance to be admitted.[47] I form the

[43]Startup proposing means that the startups take the initiative to apply for accelerators and accelerators decide which startups to admit. Please refer to Gale and Shapley [72] for the details.

[44]However, there is evidence that accelerators, even Y Combinator, will send invitations to startups (Stross [141]). I also conduct a version of simulation with accelerators proposing. Although startups see lower match values on average, the general pattern of the results hold.

[45]Using observed data also causes difficulty to simulate the error term. Because of sorting, the unobserved quality associated with admitted startups are drawn from the right of an unknown threshold of the underlying distribution.

[46]Another way to simulate the data is to use the accelerator participants' characteristic changes over the years. This approach works well if we can assume the type and number of applicants remain similar over time. However, this assumption is not accurate. Over the years, more high-quality startups begin to participate in this market thanks to the early success of accelerators.

[47]Note that this simulation may cause a biased result if the policy intervention has a large enough impact.

benchmark, as shown in Table 1.8, with simulated dataset and model estimates for all policy evaluations. The caveat notwithstanding, evaluating outcomes with the same equilibrium forming mechanism with simulated dataset serves to illustrate the countervailing forces that shape interactions between market structure and policy interventions.

1.6.1 Equity-free Accelerator

Many institution-backed accelerators offer free seed (no equity) as a grant for their participants. Like a scholarship to the startups, this policy hopes to attract more entrepreneurs from the subsidized community by lowering their cost to participate in accelerators. In this counterfactual, I impose policies under which accelerators do not take any equity from the subsidized startups. The subsidy compensates accelerators' loss, which is the original equity share times the expected startup value at graduation. As a result, this subsidy changes the preference of startups but not that of accelerators.

Table 1.9 reports the impacts on participants of subsidized accelerators. I find neither of the three types of subsidies significantly change the admission rates of female entrepreneurs, first-time founders, and startups founded outside of startup hubs in accelerators. The intuition is that increasing the willingness of startups which face challenges to join accelerators does not increase the competitiveness of these startups from the accelerator perspective. Therefore the accelerators will not admit more entrepreneurs who have disadvantages in accelerators although they may see more applications from those entrepreneurs.

To illustrate the policy's impact on startup value, Table 1.9 also reports the calculated value changes based on the deterministic part. Note that although the calculated startup

For example, if a subsidy gives every female founder a $10m capital injection, the accelerators will be full of firms founded by women. The accelerators will also attract very high-quality startups, which would not want to join accelerators otherwise. If there are not enough high-quality female-led startups, accelerators will also admit low-quality female-led startups, which would not be admitted without the subsidy. The simulated data does not capture either the high or low-quality startups. In this paper, I only test the policies which cause marginal changes.

values are lower than the real expected values by abstracting away from the unobserved quality, the value changes due to the policy are not necessarily biased.

Based on the deterministic startup values and the equity share, the average cost due to the subsidies is at around \$100k for each subsidized startup for all three types of policies. While "Gender Subsidy" has almost no impact on the startup value, "Exp Subsidy" and "T3 subsidy" increase the value of subsidized startups, but the level of improvement is no higher than the amount of subsidy size.

1.6.2 Capital Injection

Because reducing the participation cost is not an effective means to assist entrepreneurs with disadvantages in accelerators, I examine another potential subsidy which offers additional capital for startups after graduation. Such direct capital injections to startups, similar to the Start Fund for Y Combinator in 2011, have become popular in top accelerators (e.g., TechStars followed Y Combinator in 2012) but are rare in other programs. In this counterfactual, I examine the impacts of providing a grant of \$150k to entrepreneurs with disadvantages. Compared with the previous approach, this subsidy cost is about 50% higher. [48] Based on the equity share, the startup value increase due to the capital injection changes the preferences of both accelerators and startups.

As shown in Table 1.10, "Gender Subsidy" creates little change in the participants' profile and startup values. One reason is that the disadvantage of women in Tier 1 is substantial compared with the subsidy size. With a relatively milder weakness in Tier 3, first-time founders see a significant increase, by about 3.5%, in admission rates in Tier 3 under the "Exp Subsidy". Because women tend to be inexperienced, the "Exp Subsidy" also increases the admission rates of female-led startups by 7.1% in Tier 3. By subsidizing all startups

[48] The real cost increase is likely to be lower than 50% because the calculation in previous approach ignores the unobserved quality.

from Tier 3 accelerators outside of startup hubs, "T3 Subsidy" does not increase admission rates of female or first-time entrepreneurs. Because the subsidy size is small compared with the relocation cost, this support does not raise the participation rates of startups founded in startup hubs either.

With higher costs, the capital injection approach generates higher increases in startup values. However, the improvements are not substantial, and no increase is larger than the subsidy size.

1.7 Startup Performance After Accelerators

A fundamental assumption of my empirical approach is that the revealed preference reflects the accelerator's ability to level the difference between startups. This section provides a validity check on this assumption by studying the performance variation across startups after experience with accelerators. I examine how two outcome measures - financing and acquisition - depend on the accelerator and startup factors.

The popular diff-in-diff approach to study startup performance after accelerators in prior literature (e.g., Hochberg [90], Yu [151]) is improper to examine the variation among accelerators because of the presence of sorting. With the matching estimates, I propose a method, which is similar to the approach in Akkus et al. [5], to control for the unobserved heterogeneity in regressions.

1.7.1 Model Setup

The concern over using traditional methods like OLS to study the accelerator impact relates to the endogeneity in the unobserved term. Take the OLS for example.[49] For a given startup performance measure, PF (e.g., funding probability), and the match between a and s, the

[49] It is also applicable to other similar methods such as Logit and Probit.

OLS estimates $PF_{as} = Z^{as}\delta + t^{as}$, where Z^{as} is a vector of observed covariates and t^{as} is the unobserved term. To generate consistent estimates, the OLS requires that t^{as} to be independent of Z^{as}, which is satisfied if the accelerators and startups are matched purely based on Z^{as} (i.e., the researcher can fully capture the agent's decision through observables). However, this is not accurate in the accelerator market, and we have PF_{as} correlates with the matching value U_{as} through the unobserved terms. In other words, the correlation between ε^{as} and t^{as} is not zero.

Note that we can write $PF_{as} = Z^{as}\delta + t^{as} = Z^{as}\delta + \gamma\varepsilon^{as} + e^{as}$, where γ is the correlation between ε^{as} and t^{as}, and e^{as} is i.i.d.. Given $\varepsilon^{as} = U_{as} - X^{as}\beta$ as in the matching model, we have $PF_{as} = Z^{as}\delta + \gamma(U_{as} - X^{as}\beta) + e^{as}$, which can be consistently estimated if one observes U_{as}. Following Akkus et al. [5], I use a proxy P_{as} for U_{as} as $U_{as} = P_{as} + v_{as}$, where v_{as} is independent of P_{as}, Z^{as}, and X^{as}. In this way, $PF_{as} = Z^{as}\delta + \gamma(P_{as} - X^{as}\beta) + \xi_{as}$ with $\xi_{as} = (e^{as} + \gamma v_{as})$ and ξ_{as} is independent of P_{as}, Z^{as}, and X^{as}. In this paper, I let P be the dummy of startup survival (either has been acquired or in operation) status five years after graduation. Other alternatives and robustness check will be discussed in the appendix.

In summary, the second stage estimation is:

$$PF_{as} = Z^{as}\delta + \gamma\left[P_{as} - (X^{as}\beta)\right] + \xi_{as}$$

1.7.2 Model Results

I examine the accelerator's impact on startup performance through two measures. The first measure is the external financing captured through an indicator variable on whether the firm obtains venture financing after graduation. I collect this information from CrunchBase and cross check it with CBinsights and Capital IQ for accuracy. When no funding information is found, I assume the company has not raised any money. Alternatively, I can use the funding size as a measure. However, since the equity information is mostly missing, this measure is subject to considerable noise.

Given that acquisition statistics are often cited when accelerators speak to the performance of their portfolio companies, it is an important metric of success(Yu [151]).[50] Acquired is a binary variable, with 1 indicating that a company has been acquired and 0 indicating that a company has not been acquired.[51] I collect the acquisition information mainly from the Crunchbase and CapitalIQ. I cross check them from the company websites and the founders' Linkedin pages.

For independent variables, I include the same set of factors as in the matching model. To avoid the interpretation challenge caused by the "Start Fund" factor, I exclude the cohort that received the Start Fund investment in this stage.[52]

I examine four types of models in this stage. Table 1.11 shows results for the first three models. The first model studies the accelerator impact on firm financing probability within one-year after graduation. The second model examines startups' long-term (i.e., 2nd to 5th year after graduation) financing rates given they were founded within one year after graduation. The third model is the same as the second except it is for firms that did not get funded within one year after graduation. Table 1.12 reports estimates for the last model, which studies the acquisition rates. Across all models, the coefficients of $(Proxy - MatchingValue)$, which proxies for the ε_{as} in the matching model, indicate significant positive sorting in the market.

In regards to fundraising, female entrepreneurs and first-time founders have no disad-

[50] One caveat of this measure is that acquisitions do not always happen because the target firm is of high quality. Sometimes a startup is acquired for its technology or human capital despite its poor performance. The failure rates are also an appealing statistic to test. However, it is unclear whether a fast failure in the accelerator market is necessarily bad. Yu [151] argues the accelerator creates value by allowing low-quality businesses to fail faster.

[51] I do not use Initial Public Offering (IPO) because there is only one such case.

[52] With the presence of "Start Fund", the dependent variable captures the additional effects since the graduates have already been funded by "Start Fund". Although not reported, I tested the case with "Start Fund" and all the following results hold with slightly different magnitudes. The coefficient of "Start Fund" is negative but insignificant.

vantages in the short-term. Female entrepreneurs even tend to perform better in a larger cohort. Over the long-term, while female founders still see no disadvantage, younger entrepreneurs tend to outperform. Startups founded outside startup hubs have less of a chance to obtain venture financing. Older startups have a higher chance to be more successful in the short-term, but their advantages disappear in the long-term. These results are consistent with the findings in the matching model.

The coefficients of accelerator tier dummies indicate that Tier 1 and 2 have significantly higher impacts on the venture financing in the short-term. In the long-term, I find the Tier 1 and 2 accelerators' impact persists over time for startups that obtained fundraising in the short-term. In addition, the accelerator's impact is not due to the improved financing in the short-term. On the other hand, I do not find Tier 1 and 2 have advantages for startups who do not obtain financing in the short-term. While Tier 1 and 2 graduates still have a higher chance of survival (Tier 1 56%, Tier 2 42%, Tier 3 41%) and raising funds, this difference is small and seems to be caused by the sorting effect as suggested by the last model in Table 1.11.

The findings in Table 1.12 for acquisition rates are similar to the long-term financing except that I do not find a significant difference among accelerators. One potential reason is that the most successful graduates, especially those from top accelerators, operate on their own. While the acquisition rates may still be a useful metric to evaluate some accelerators, they are not accurate when comparing the difference between different tiers.

For comparison, I report results for "naive" methods without controlling for sorting in unobserved heterogeneity in Table 1.12. Similar results for Table 1.11 models can be found in Table 1.4. Across these models, the estimates for the physical distance, as captured by "Out-of-State Participant", are the most obvious differences. Further, the advantage of Tier 1 and 2 programs remain the same or even decreases after control for sorting, especially in the long-term. Considering the non-trivial positive sorting as suggested by the parameter of $(Proxy - MatchingValue)$, this finding suggests that the top accelerators tend to pick those startups with lower expected quality captured by the unobservable factors, which may seem bizarre at first glance. One explanation is that these are firms with high risk but also high potential return if successful. Since Tier 1 and 2 programs may have the best pick in the market and are more confident in their ability, they can afford to take these candidates.

1.8 Conclusion

This paper studies the ability of accelerators to level the playing field for startups by reducing the correlation between a startup's growth opportunity and its founder's demographic characteristics. I develop a novel framework to estimate the preference of for-profit accelerators in the admission process. My results suggest that female founders have no disadvantage in accelerators, except in the top programs. High-quality accelerators can alleviate the human capital difference between experienced and inexperienced entrepreneurs. And, the accelerator alone cannot entirely replace the support from a better environment in startup hubs like Silicon Valley. Though counterfactuals, I find that equity-free accelerators does not increase admission rates of female entrepreneurs, first-time founders, or founders not present in startup hubs. Direct capital injection to inexperienced entrepreneurs can raise the admission rates of first-time founders as well as female founders.

The proposed NTU matching estimator extends the empirical NTU matching literature by generating consistent estimates with only endogenously selected observations. With the identification relying on variations in the fixed utility sharing rule, this method is applicable to similar settings such as the school-student market. For example, while prior literature studying the impacts of scholarship on college participation focuses the extensive margin (e.g., Dynarski (2003); Dynarski (2002)), the framework of this paper allows researchers to examine the internal dynamics of the market participants (i.e., do more minorities join better colleges due to the impact of scholarships?).

Table 1.1: Accelerator Profiles Across Tiers

Note: The accelerator participants are early-stage startups - mostly firms before any venture capital financing. The majority of these early accelerators focuses on high-tech startups, especially in information technology related fields. Better accelerators, as indicated by the tiers, tend to take lower equity and have bigger classes. Furthermore, the best accelerators take low equities from firms but do not give the highest seed investment. The second tier programs are the most generous in terms of firm valuation, taking low equity and giving high seeds. On average, the entrepreneurs who participate in accelerators are significantly younger than the non-participants (close to 40). Further, while some argue accelerators are for first-time entrepreneurs, one-third of participants have founded some company before.

	Tier 1	Tier 2	Tier 3
# of Accelerators	2	8	17
# of Programs	19	25	30
# of States Represented	5	6	15
# of Programs in Startup Hubs (CA, NY, MA)	13	8	6
Equity Range	5%~6%	5%~8%	5%~10%
Seed Investment Range	10k~20k	10k~50k	6k~25k
Average Valuation (Seed/Equity)	307.9k	364.2k	274.9k
Average Cohort Size	26.72	13.12	8.01
# of Startups	335	239	202
Startup Average Age	1.83	1.73	1.77
Average Founder Age	27.81	29.37	29.68
Inexperienced Team	61.49%	63.18%	61.39%
Female Founder in Team	4.78%	13.81%	9.90%
Graduate Degree Founder in Team	30.45%	39.75%	36.63%
Industry: IT/Software	46.27%	44.77%	52.48%
Industry: Social Media/Social Platform	16.71%	18.83%	19.31%
Industry: Healthcare/Education	4.78%	9.21%	7.43%
Industry: Others	32.24%	27.19%	20.78%

Table 1.2: Accelerator Performance Across Tiers

Note: "In Operation Rates" represents the percentage of firms still in operation and not acquired five years after graduation. "Acquisition Rates" represents the percentage of firms that have been acquired within five years after graduation. "One-Year" and "Five-Year" show the startup performance within one year and five years after graduation respectively.

	Tier 1		**Tier 2**		**Tier 3**	
	Mean	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
Startup Operation Status (Five Year)						
In Operation Rates	49.25%	2.73%	58.16%	3.19%	47.52%	3.51%
Acquisition Rates	28.36%	2.46%	20.50%	2.61%	13.36%	2.39%
Startup Funding Rates						
One-Year	52.24%	2.73%	47.28%	3.23%	25.74%	3.08%
Five-Year	58.21%	2.69%	53.97%	3.22%	32.67%	3.30%
Startup Funding Sizes Given Funded (k$)						
One-Year	1,696	2,216	956	1,432	986	1,272
Five-Year	16,135	59,890	5,549	13,147	6,802	18,104

Table 1.3: Reduced-Form Evidence: Probit of Chosen By Accelerators

Note: The stars indicate significance level (* for 90%, ** for 95%, and *** for 99%). Assuming accelerators are the only decision-makers in the admission market, one can use a Probit model to study the revealed preference of accelerators with results shown in this table. Specifically, I form all potential matches between accelerators and startups and construct the dependent variable as the indicator of whether the match is observed in data. Although this estimation is biased due to the correlation among unobserved terms, we still find some assortative patterns such that relocation is costly and Tier 1 creates higher value for inexperienced entrepreneurs. $R^2 = 0.27$.

Variables	**Coef**	**Std. Err.**
Panel A: Startup Factors		
Female Founder(s)	-0.11	0.28
Inexperienced Founder(s)	-0.28**	0.11
Founded Outside Startup Hubs	0.50***	0.05
0.01*Average Founder Age	-0.01***	0.00
Startup Age	0.00	0.02
Panel B: Complementarities		
log(Cohort Size)*Female Founder	0.03	0.13
Tier 1*Female Founder	-0.22	0.23
Tier 2*Female Founder	0.16	0.18
log(Cohort Size)*Inexperienced Founder	0.07	0.05
Tier 1*Inexperienced Founder	0.45***	0.08
Tier 2*Inexperienced Founder	-0.02	0.07
Out-of-State Participant	-1.62***	0.05
Constant	-0.64***	0.12
Observations	19,096	

Table 1.4: Reduced-Form Evidence: Short-Term Financing, Long-Term Financing, and Survival

Note: The stars indicate significance level (* for 90%, ** for 95%, and *** for 99%). "Crisis & One Year Aft Crisis" equals to one if the accelerator program happens before July 2010, which is one year after the official end of the great recession of NBER definition. This table shows the regression results of four models. The first model "ST financing" has the independent variable of indicators on whether the startup obtained venture financing within one year after graduation. The "LT Financing 1" has independent variables of indicators on whether the firm, which was funded within one year after graduation, obtained venture financing between 2nd-5th year after graduation. The "LT Financing 2" has the independent variable of an indicator on whether the firm, which was NOT funded within one year after graduation, obtained venture financing between 2nd-5th year after graduation. The last model has the independent variable of an indicator as to whether the firm survived within 5-year after graduation. I exclude the cohort which received Start Fund investment to avoid biased estimation.

Variables	**ST Financing**		**LT Financing 1**		**LT Financing 2**		**Survival Rate**	
	Coef	**Std. Err.**	**Coef**	**Std. Err.**	**Coef**	**Std. Err.**	**Coef**	**Std. Err.**
Panel A: Startup Factors								
Female	0.01	0.12	0.34	0.27	-0.05	0.13	-0.11	0.12
Inexperienced	-0.01	0.07	0.30**	0.15	-0.10	0.08	-0.02	0.07
Founded Outside Startup Hubs	-0.06	0.04	-0.04	0.07	-0.09	0.06	0.02	0.04
0.01*Avg Founder Age	0.15	0.34	0.01	0.61	-0.21	0.39	0.90***	0.34
Startup Age	0.07***	0.02	0.02	0.03	0.00	0.03	0.04*	0.02
Panel B: Accelerator Factors								
log(Cohort)	-0.01	0.07	-0.07	0.11	0.04	0.09	0.08	0.07
Tier 1	0.32***	0.09	0.41***	0.15	-0.05	0.13	0.15	0.09
Tier 2	0.22***	0.08	0.29**	0.15	-0.11	0.09	0.09	0.08
Panel C: Complementarities								
log(Cohort)*Female	0.24*	0.12	0.35	0.23	-0.05	0.16	0.13	0.12
Tier 1*Female	-0.02	0.19	-0.22	0.33	0.26	0.28	0.22	0.19
Tier 2*Female	-0.07	0.16	-0.63*	0.35	-0.11	0.17	-0.02	0.16
log(Cohort)*Inexp	0.03	0.08	-0.03	0.14	-0.07	0.11	0.05	0.08
Tier 1*Inexp	-0.04	0.12	-0.35*	0.19	0.15	0.15	0.04	0.12
Tier 2*Inexp	-0.04	0.10	-0.34*	0.19	0.20*	0.12	-0.05	0.10
Out-of-State Participant	0.02	0.04	-0.05	0.07	0.10*	0.05	-0.03	0.04
Panel D: Other Match Specifics								
Crisis & One Yr Aft Crisis	-0.22***	0.04	0.02	0.08	-0.06	0.05	-0.07	0.04
Constant	0.21	0.13	0.22	0.24	0.39***	0.14	0.24*	0.13
Observations	648		274		368		648	

Table 1.5: Matching Model Results

Note: ** indicates within 95% CI. "Crisis & One Year Aft Crisis" equals to one if the accelerator program happens before July 2010, which is one year after the official end of the great recession of NBER definition. Model 1 includes no interactions between observed factors of the two sides of the market. Model 2 extends Model 1 to study the heterogeneity with interactions. Normalizing the startup age to have parameter of ± 1, I estimate the matching models (first and third stages) by running the differential evolution optimization routine from 40 different starting points (20 each for the positive and negative normalization respectively) and selecting the coefficient vector that yields the highest value for the objective function. For valid inference, I generate the confidence intervals using the subsampling procedure described by Politis and Romano [129] and Delgado et al. [51] to approximate the sampling distribution. I randomly conduct 100 of these subsamples with size at about one third of the total data set. For each of the subsamples, I estimate the parameter vector as for the whole dataset. Call the estimate from the sth subsample $\hat{\beta}_s$ and the estimate from the original full sample β. The approximate sampling distribution for the parameter vector can be computed by calculating $\tilde{\beta}_s = (n/N)^{1/3}(\hat{\beta}_s - \beta) + \beta$ for each subsample, where N and n_s are the total sample size and given subsample size respectively. I take the 2.5th percentile and the 97.5th percentile of this empirical sampling distribution to compute 95% confidence intervals for all of the estimates. For a convenient interpretation, I re-normalize the coefficient in the right most column to the dollar value based on the "Start Fund" parameter, which represents a USD 150k increase.

Variables	**Model 1**			**Model 2**			
	Coef	**C.I. (95%)**		**Coef**	**C.I. (95%)**		**Coef $m**
Panel A: Startup Factors							
Female	-3.09**	-5.58	-1.88	-5.29**	-22.28	-0.06	-0.12
Inexperienced	-0.02	-0.19	0.07	-13.32**	-16.38	-0.38	-0.30
Founded Outside Startup Hubs	2.46**	1.01	11.13	-4.95**	-10.03	-0.21	-0.11
0.01*Avg Founder Age	2.30	-2.73	3.28	0.58	-3.41	2.26	0.01
Startup Age	1	super consistent		1	super consistent		0.02
Panel B: Accelerator Factors							
log(Cohort)	-7.49**	-11.34	-7.42	-4.12**	-9.62	-3.86	-0.09
Tier 1	11.65**	11.45	17.75	10.21**	10.11	29.83	0.23
Tier 2	2.93**	1.85	4.49	5.40	-0.79	22.17	0.12
Start Fund	5.26**	4.00	8.08	6.64**	4.22	16.78	0.15
Seed	1.88**	0.58	8.57	1.72**	0.56	35.12	0.04
Panel C: Complementarities							
log(Cohort)*Female				4.12**	3.14	9.65	0.09
Tier 1*Female				-20.63**	-39.75	-9.20	-0.47
Tier 2*Female				-5.87	-12.68	11.33	-0.13
log(Cohort)*Inexp				-0.13	-2.99	0.55	0.00
Tier 1*Inexp				13.50**	1.51	15.65	0.30
Tier 2*Inexp				13.61**	0.71	15.36	0.31
Out-of-State Participant	-16.20**	-24.57	-16.03	-29.51**	-42.87	-26.63	-0.67
Panel D: Other Match Specifics							
Crisis & One Yr Aft Crisis	2.41**	1.13	9.52	12.86**	3.85	23.02	0.29
Constant	46.24**	45.59	64.10	79.93**	77.50	83.45	1.81
Matching Score	81.11%			81.18%			

Table 1.6: Summary of Match Values

Note: This table reports the total match surplus of observed matches between startups and accelerators. All these values are calculated with the estimates in Table 5 Model 2. It is renormalized to million USD based on the importance of USD 150k capital through the Start Fund. The mean differences among all three tiers are significant at 99%. For comparison, the last column reports the average startup valuation in million USD calculated based on the accelerator's seed and equity-share. Note that the calculated value ignores the unobserved quality and therefore likely to be downward biased due to selection. Further, because of sorting, this bias tends to be larger in better accelerators.

	Obs	**Mean (m$)**	**Std. Dev**	**Seed/Equity**
Tier 1 Accelerators	319	1.73	0.31	0.31
Tier 2 Accelerators	226	1.50	0.37	0.36
Tier 3 Accelerators	191	1.24	0.34	0.27
All Accelerators	736	1.53	0.39	0.32

Table 1.7: Examples of Policy Intervention Effects

Note: This table shows two examples to illustrate the complexity of the equilibrium conditions of NTU two-sided matching, which makes the effect of policy intervention on the accelerator market hard to predict. In both cases, I assume the utility share between accelerators and firms are fixed and the same for all participants so that the total match utility determines the matching pattern. The first column reports the match values for all potential matches in the baseline case. The third column reports the match values in the scenario with a subsidy. The second and fourth columns report the realized matches for the baseline and subsidy scenario respectively. In example 1, the subsidies to both accelerators decreased the total welfare of the market by making one of the accelerators worse off; In the second example, a subsidy to only one of the accelerators makes all market participants better off.

	Original Match Utility	**Match**	**Subsidized Match Utility**	**Match**
Example 1:				
Accelerator A - Firm 1	9	✓	10	
Accelerator A - Firm 2	8		11	✓
Accelerator B - Firm 1	0		2	✓
Accelerator B - Firm 2	8	✓	10	
Example 2:				
Accelerator A - Firm 1	6	✓	6	
Accelerator A - Firm 2	9		9	✓
Accelerator B - Firm 1	8		12	✓
Accelerator B - Firm 2	10	✓	11	

Table 1.8: Startup Characteristic Moments of Simulated Dataset

Note: The firm value represents the average startup share of the graduation value. I use the Gale and Shapley [72] algorithm to form matches with startups proposing, which is likely to be close to the reality given the low acceptance rate of accelerators. Because it generates the startup-optimal matching (Roth and Sotomayor [135]), this approach is in line with the purpose of the policy interventions to improve the startup growth. I simulate 750 firms each year across four years, and the firm characteristics are generated based on the estimated joint distribution of data. Although the simulated dataset is not representative to the population of all accelerator applicants, it is likely to capture the features of those high-quality startups which are more likely to be admitted. I simulate the error terms 200 times with a normal distribution with mean zero and the standard deviation of one.

	Tier 1		**Tier 2**		**Tier 3**	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Firm Value in m$	1.74	0.01	1.60	0.01	1.40	0.01
Female Founder	6.74%	1.10%	8.53%	1.40%	9.51%	1.47%
Experienced Founder	36.31%	1.94%	39.51%	2.30%	43.81%	2.75%
Startup Founded in Startup Hubs	59.70%	1.81%	48.38%	2.35%	39.90%	2.31%
Average Founder Age	28.52	0.21	29.39	0.26	29.24	0.32
Startup Age	1.78	0.03	1.83	0.04	1.71	0.05

Table 1.9: CF1: Replace Equity Funding With Grants

Note: * indicates within 95% CI. "SH" represents in startup hubs. "N-SH" indicates for accelerators not in startup hubs. "Base" is the baseline scenario and "CF" indicates the counterfactual analysis results. This table shows the changes concerning firm values and startup factors for each policy intervention based on the simulated benchmark. In this counterfactual, I impose policies to offer equity-free accelerators to entrepreneurs with disadvantages in accelerators. Under these policy interventions, accelerators do not take any equity from the subsidized startups and compensate for the loss, which is the original equity share times the expected startup value at graduation, from the subsidy. As a result, this subsidy changes the preference of startups but not that of accelerators. The first policy called "Gender Subsidy" supports female applicants to Tier 1. The second policy called "Exp Subsidy" assists first-time founders to increase their opportunity to enter Tier 3. The last policy called "T3 Subsidy" aims to help Tier 3 accelerators located outside of startup hubs.

Accelerator Participants	**Gender Subsidy**			**Exp Subsidy**			**T3 Subsidy**		
	Base (T1)	**CF**	**Change**	**Base (T3)**	**CF**	**Change**	**Base (NSH)**	**CF**	**Change**
Avg Value ($m)	1.74	1.74	+0.00	1.40	1.43	+0.02*	1.40	1.49	+0.08*
Avg Subsidized Value ($m)	1.68	1.69	+0.01	1.40	1.42	+0.02*	1.36	1.46	+0.10*
Female	23.74	23.69	-0.05	19.71	19.72	+0.01	19.72	19.73	+0.01
Inexp	224.19	224.13	-0.06	116.39	116.36	-0.02	116.36	116.49	+0.12
#Founded NSH	141.87	141.97	+0.10	124.37	124.34	-0.02	124.34	124.45	+0.11

Table 1.10: CF2: Capital Injection

Note: * indicates within 95% CI. "SH" represents within startup hubs. "Base" is the baseline scenario and "CF" indicates the counterfactual analysis results. This table shows the changes concerning firm values and startup factors for each policy interventions based on the simulated benchmark. In the second counterfactual, I evaluate the policy interventions to provide a grant of $150k to startups but do not change the equity funding structure. Compared with the previous approach, these types of policy often involve bigger subsidies because part of the support indirectly goes to accelerators due to the equity share. These grants change the preference of both accelerators and startups. The first policy called "Gender Subsidy" supports female applicants to Tier 1. The second policy called "Exp Subsidy" assists first-time founders to increase their opportunity to enter Tier 3. The last policy called "T3 Subsidy" aims to help Tier 3 accelerators located outside of startup hubs.

Accelerator Participants	**Gender Subsidy**			**Exp Subsidy**			**T3 Subsidy**		
	Base (T1)	**CF**	**Change**	**Base (T3)**	**CF**	**Change**	**Base (NSH)**	**CF**	**Change**
Avg Value ($m)	1.74	1.74	+0.00	1.40	1.44	+0.03*	1.40	1.52	+0.11*
Avg Subsidized Value ($m)	1.68	1.69	+0.01	1.40	1.43	+0.03*	1.36	1.50	+0.14*
Female	23.74	23.79	+0.06	19.67	21.09	+1.42*	19.70	19.78	+0.09
Inexp	224.19	224.01	-0.18	116.46	120.41	+3.95*	116.32	116.55	+0.23
#Founded NSH	141.87	142.09	+0.22	124.32	124.91	+0.59	124.40	124.45	+0.05

Table 1.11: Startup Performance: Financing

Note: The stars indicate significance level (* for 90%, ** for 95%, and *** for 99%). "Crisis & One Year Aft Crisis" equals to one if the accelerator program happens before July 2010, which is one year after the official end of the great recession of NBER definition. This table shows the regression results of three models. The first model "ST financing" has the independent variable of indicators on whether the startup obtained venture financing within one year after graduation. The "LT Financing 1" has independent variables of indicators on whether the firm, which was funded within one year after graduation, obtained venture financing between 2nd-5th year after graduation. The additional control of log(fund size within 1yr aft graduation) controls for the impact of funding size in the short-term. The "LT Financing 2" has the independent variable of an indicator on whether the firm, which was NOT funded within one year after graduation, obtained venture financing between 2nd-5th year after graduation. I exclude the cohort which received Start Fund investment to avoid biased estimation. The positive parameter for (Proxy-Match Value) suggests a positive sorting pattern.

Variables	**ST Financing**		**LT Financing 1**		**LT Financing 2**	
	Coef	**Std. Err.**	**Coef**	**Std. Err.**	**Coef**	**Std. Err.**
Unobserved Sorting: (Proxy-Matching Value)	0.35***	0.04	0.41***	0.08	0.45***	0.04
log(Fund Size Within 1yr Aft Graduation)			0.06**	0.03		
Panel A: Startup Factors						
Female	0.06	0.11	0.40	0.25	0.02	0.11
Inexperienced	-0.04	0.07	0.20	0.14	-0.12*	0.07
Founded Outside Startup Hubs	-0.08**	0.04	-0.05	0.07	-0.14***	0.05
0.01*Average Founder Age	-0.15	0.32	-0.26	0.57	-0.70**	0.33
Startup Age	0.06***	0.02	0.01	0.03	0.00	0.02
Panel B: Accelerator Factors						
log(Cohort)	-0.04	0.06	-0.13	0.10	0.00	0.08
Tier 1	0.31***	0.09	0.35**	0.14	0.02	0.11
Tier 2	0.22***	0.08	0.28*	0.14	-0.05	0.08
Panel C: Complementarities						
log(Cohort)*Female	0.21*	0.11	0.38*	0.22	-0.06	0.14
Tier 1*Female	-0.17	0.18	-0.37	0.31	0.03	0.23
Tier 2*Female	-0.08	0.15	-0.70*	0.33	-0.14	0.14
log(Cohort)*Inexp	0.01	0.08	-0.01	0.13	-0.11	0.09
Tier 1*Inexp	-0.01	0.11	-0.25	0.18	0.15	0.13
Tier 2*Inexp	0.03	0.10	-0.22	0.18	0.25**	0.10
Out-of-State Participant	-0.07*	0.04	-0.12*	0.07	-0.05	0.05
Panel D: Other Match Specifics						
Crisis & One Yr Aft Crisis	-0.16***	0.04	0.08	0.07	0.00	0.04
Constant	0.36***	0.12	-0.07	0.28	0.63***	0.12
Observations	648		274		368	

Table 1.12: Startup Performance: Five-Year Exit Rate

Note: The stars indicate significance level (* for 90%, ** for 95%, and *** for 99%). “Crisis & One Year Aft Crisis” equals to one if the accelerator program happens before July 2010, which is one year after the official end of the great recession of NBER definition. This table shows the regression results of four models. The first model has the independent variable of an indicator on whether the firm is acquired within 5-year after graduation. The second model shows comparable results without control for sorting. The third model has the independent variable of an indicator on whether the firm, which was NOT funded within one year after graduation, is acquired during 5-year after graduation. The last model studies a similar setting as in the third model but for firms obtained financing within one year after graduation. I exclude the cohort which received Start Fund investment to avoid biased estimation. The positive parameter for (Proxy-Match Value) suggests a positive sorting pattern.

Variables	**Ctl Sorting**		**Not Ctl Sorting**		**Not Funded ST**		**Funded ST**	
	Coef	**Std. Err.**	**Coef**	**Std. Err.**	**Coef**	**Std. Err.**	**Coef**	**Std. Err.**
Unobserved Sorting: (Proxy-Matching Value)	0.35***	0.03			0.30***	0.03	0.38***	0.08
Panel A: Startup Factors								
Female	0.09	0.10	0.04	0.11	0.09	0.10	0.10	0.24
Inexperienced	-0.11*	0.06	-0.08	0.07	-0.11*	0.06	-0.16	0.14
Founded Outside Startup Hubs	-0.08**	0.04	-0.06	0.04	-0.10**	0.04	-0.01	0.07
0.01*Average Founder Age	-0.71***	0.28	-0.42	0.30	-0.55*	0.29	-0.76	0.55
Startup Age	0.00	0.02	0.01	0.02	0.01	0.02	-0.01	0.03
Panel B: Accelerator Factors								
log(Cohort)	0.02	0.06	0.05	0.06	0.03	0.07	-0.03	0.10
Tier 1	0.03	0.08	0.04	0.08	0.04	0.09	0.01	0.14
Tier 2	0.03	0.07	0.03	0.07	-0.08	0.07	0.14	0.14
Panel C: Complementarities								
log(Cohort)*Female	-0.01	0.10	0.02	0.11	-0.06	0.12	-0.03	0.21
Tier 1*Female	-0.10	0.15	0.05	0.17	0.08	0.20	-0.20	0.30
Tier 2*Female	-0.10	0.13	-0.09	0.14	-0.11	0.12	-0.09	0.32
log(Cohort)*Inexp	-0.07	0.07	-0.05	0.07	-0.11	0.08	0.04	0.12
Tier 1*Inexp	0.15*	0.09	0.12	0.10	0.12	0.11	0.21	0.18
Tier 2*Inexp	0.12	0.08	0.06	0.09	0.22***	0.09	0.03	0.17
Out-of-State Participant	-0.08**	0.04	0.01	0.04	-0.01	0.04	-0.17***	0.06
Panel D: Other Match Specifics								
Crisis & One Yr Aft Crisis	0.04	0.04	-0.03	0.04	-0.01	0.04	0.14*	0.07
Constant	0.49***	0.10	0.35***	0.11	0.43***	0.11	0.53**	0.22
Observations	648		648		368		274	

Figure 1.1: Accelerator Process

This figure shows the flowchart of the accelerator process. The whole procedure of accelerators starts with a public announcement of the details and terms of the program, such as application requirements, resources provided, seed investment, equity share, class size, location, and schedule. Once announced, these terms stay the same for all participants. Entrepreneurs submit their applications as individual firms. Admitted entrepreneurs start the program together at the same time and in the same location. The program lasts for a fixed period, often three months, during which accelerators offer mentorship, network opportunities, and other forms of business support. At the end of the program, accelerators hold a "Demo Day" in which each startup pitches to a group of potential investors. Firms are officially off the hook in terms of participating in accelerator after graduation, but they can, and often do, become involved in the alumni community.

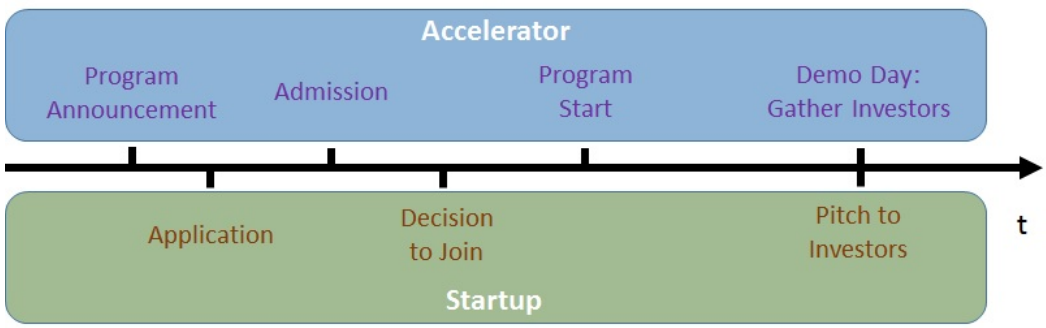
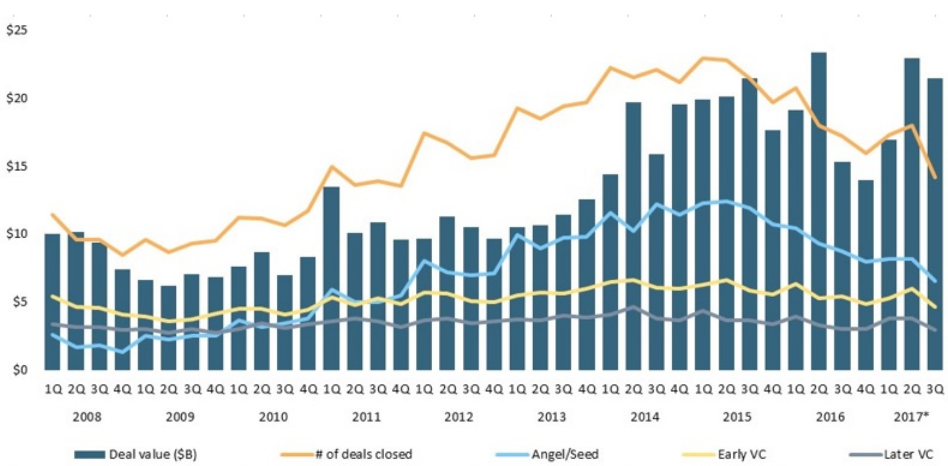


Figure 1.2: PitchBook Data on Venture Financing Deals

This diagram (source: pitchbook.com) shows venture financing trends over the past decade in the U.S. While venture investment deals reverted to the upward trend in 2009, the recovery only began to speed up since the third quarter of 2010. This is especially true of the market for early startups, which is indicated by “Angel/Seed” and “Early VC”.



Chapter 2

How Business Accelerators Accelerate Startups: Screening vs. Training

With screening and business training, business accelerators have become an essential player in the entrepreneurship world in the past decade. I study the relative importance of screening in accelerator value creation from the market participant's perspective. In a competitive market, any value creation for startups through screening should be reflected in the increase of venture financing in the short term after accelerator graduation. I develop a three-stage approach to identify the upper bound of screening's value creation by examining the importance of the accelerator's ability to assist startup fundraising in the short run. With a novel dataset, covering the universe of U.S. business accelerators from 2008 to 2011, I find the screening contributes to less than 1/6 of the total value added by accelerators on average, and the ratio is meager, at 1/10, for the top accelerators.

2.1 Introduction

Over the past decade, business accelerators have become essential players in the entrepreneurship market. This new mechanism attracts not only investors, aiming for higher returns, but also institutions and local governments, who hope to boost their communities' economies. Business accelerators provide startups with assistance on venture financing and managerial capital.[1] [2] They create value through two mechanisms - screening, which creates a startup quality certificate to reduce market information asymmetry, and training, which improves entrepreneurs' ability to run businesses. These two channels have different implications for society. Screening improves resource reallocation efficiency but with negative spillover effect, and training directly increases social productivity but may take a longer time to realize.[3] This paper studies the relative importance of screening in the value added by business accelerators.

Business accelerators ("accelerator" hereafter) are structured programs offering fixed-term and cohort-based training, which includes mentorship, educational components, and shared-office space to participants in exchange for a small share of equity, typically 5%. Unlike traditional venture capitals, accelerators contribute little through a direct capital injection.[4] Rather, accelerators serve as intermediaries connecting startups and venture investors. This mechanism helps its graduates to obtain venture investment much earlier than otherwise by reducing information asymmetry in the market. On the other hand, with economies of scale, the accelerator lowers the cost to facilitate the knowledge flow from mentors to entrepreneurs, substituting the managerial capital which otherwise may

[1]See Da Rin et al. [45] for a survey of firm financing. See Bloom and van Reenen [25] as an example of managerial capital.

[2]I define financing capital as money injection as equity investment or loan. Managerial capital captures more "soft" firm assets such as management skills and business network. Details will be provided in Section 3.

[3]See Fang [60] for a discussion.

[4]Market participants normally consider the seed as stipend during the programs (Hallen et al. [87]).

take years of operation to accumulate. Such assistance creates a boost for startup business quality, the benefit of which lasts in the long term. Prior literature (Yu [151], Hochberg [90]) has demonstrated the positive treatment effect of accelerators. However, understanding the relative importance of accelerator value creation channels is essential to finding out whether and how we can achieve its early success in the future. This paper estimates an upper bound of screening value creation.

My empirical strategy builds on the assumption that the screening effect is reflected in the improvement of venture financing in a competitive market in the short run and vanishes in the long term. In the short term, given the popularity of accelerators, information on their participants is publically available, and any improvement caused by screening should reflect in the increase of venture financing in a competitive venture investment market.[5] The accuracy and importance of the signal generated by accelerators decay over time as information on business quality is revealed through operation records; therefore the screening effect is ignorable in the long term. I obtain an upper bound for the importance of screening by studying the value added in the venture financing improvement within one year after graduation.

My approach takes three steps: First, I obtain the accelerator production function, whose output is the expected startup value at graduation. The revealed preference during the admission process of for-profit accelerators. Because the admission process is a two-sided matching game similar to the school-student market (Roth and Sotomayor [135]), traditional methods like Logit and Probit generate biased estimates. I use a new two-sided matching maximum score estimator (Fox [66], Manski [111, 112]) to account for the sorting and interdependence of agents' choice sets. Based on the pairwise comparison mechanism (Fox [64, 66], Chen [31]), this estimator imposes weak assumption on the unobservable, generates

[5]The venture investment market, especially the one for accelerator graduates, develops fast during the past decade (See pitchbook data in appendix) and involves thousands of active investors.

consistent estimates for an endogenous sample, and allows for the existence of multiple equilibria. Second, I form a measure for financing from the venture funding probability within one year after graduation based on ex-post realized investment information. I control for sorting by constructing a measure for unobserved matching quality with estimated deterministic value and a proxy for total matching value, similar to the method proposed by Akkus et al. [5]. Finally, I identify the upper bound of the screening importance in the production function based on how the financing measure affects the admission result.

With a hand-collected novel dataset covering the universe of U.S. accelerators and their graduates from 2008 to 2011, I find that screening plays a much less important role than improvement in the managerial capital in the value added by accelerators. My calculation shows that the upper bound of the "Screening to Managerial Capital Ratio" is around 20% on average. Further, the marginal importance of screening drops as the expected funding probability increases. As a result, it is not surprising to see that participants of the "superstars" - Y Combinator (YC) and Techstars - care even less, about half of the average figure, on the improved financing through screening. This importance ratio is higher for programs held outside of startup hubs (i.e., not in California, Massachusetts, or New York) and for those startups that relocated.

This paper contributes to the emerging literature studying the accelerator phenomenon. Early studies, which are primarily conceptual (Cohen and Hochberg [39], Cohen [38]), Kim [101] model accelerators as a form of certification for startup quality. More recent studies evaluate accelerators by comparing the startup companies that completed accelerator programs to those that did not. Hallen et al. [87] find that accelerators add value through mentorship while sorting and signaling effects are also present. Gonzales-Uribe and Leatherbee [81] find business training provided by a Chilean government funded accelerator has a positive impact on subsequent startup performance, but such effect does not exist for basic supports like seed injection and shared office space. Yu [151] argues that accelerators help resolve uncertainty around company quality sooner, allowing founders to make funding and exit decisions accordingly. This paper most closely relates to the recent working paper of Chen [31], which examines the heterogeneity of accelerator value creations. Expanding his two-sided matching model into a three-stage approach, this is the first study that directly examines the accelerator's value creation channels.

This paper also connects to the literature concerning the screening effect in education which has proven difficult (Fang [60]). Although for different markets, my result is close to the findings in Lange [103], which shows that screening creates less than 20% of the total value creation of education.

2.2 Institutional Details

2.2.1 What is an Accelerator

There is no official definition for the business accelerator, which is also called seed accelerator or startup accelerator, yet. Cohen and Hochberg [39] are among the first in academia to give a clear formal definition for accelerators. Different from traditional early stage financiers, education programs or incubators, they define an accelerators as "a fixed-term, cohort-based program, including mentorship and educational components, that culminates in a public pitch event or demo-day." Another definition is from seed-db.com, which is one of the biggest public resources tracking accelerators, especially in the U.S. Seed-DB defines accelerator as a program that satisfies the following criteria: 1) has an open application process; anyone with an idea can apply; 2) invests in companies, typically in exchange for equity, at pre-seed or seed stage; 3) holds cohorts or "classes" of startups, not an on-demand resource; 4) provides a program of support for the cohorts, including events and company mentoring; 5) focuses on teams, and not individual mentoring. With some minor differences, the two definitions cover very similar programs. I identify individual accelerator programs from seed-db.com.

Accelerators target early stage startups but not nascent ones. Therefore, accelerators are not for businesses worth more than tens of millions of dollars nor nascent entrepreneurs who do not have any solid product or idea yet. Following the early programs, many accelerators invest a small amount of seed money to each startup they admit in exchange for equity. But unlike many traditional venture capitals, who confidentially negotiate with entrepreneurs, accelerators set transparent but roughly fixed terms. Thanks to modern information technologies, entrepreneurs can find information about accelerators all over the country, or even the world, easily. Figure 2.1 summaries the progress of accelerators.

The whole procedure of accelerators starts with a public announcement of the details and terms about the program, including information on application requirements, resources provided, seed investment, equity share, class size, location, and schedule. Once announced, these terms are not subject to negotiation. Startups submit their applications to accelerators. The admission process is competitive. Applicants to popular programs see the acceptance rate of 1% to 2%. The average number is around 4% for the U.S. market.[6] Admitted entrepreneurs start the program together at the same time and in the same location. The program lasts for a fixed period, often three months, during which accelerators offer mentorship, network opportunities, and other business supports. At the end of the program, accelerators hold a "Demo Day" in which each startup pitches to a group of potential investors. Firms are under no obligation to accelerator after graduation but they are often involved in the alumni community.

2.2.2 Brief History and Current Status

Y Combinator launched the world's first accelerator in 2005, followed by TechStars in 2006. Both of them have evolved over the years. Y Combinator started in Cambridge, MA then

[6]Source: https://techcrunch.com/2014/04/20/who-gets-into-accelerators-persistent-men-with-saas-apps-says-study/

also in Mountain View, CA. In 2009, it consolidated to a single program in Silicon Valley with a bigger cohort size. TechStars used a different approach. It has grown to 40 different programs worldwide as of April 2018, since its first launching in Boulder, Colorado in 2006. Both remain as top accelerators. As summarized by Hathaway, the growth in U.S.-based accelerators took off after 2008.[7] The number reached 170 programs in 2014 and held mostly steady afterwards. Accelerators attract much attention thanks to their outstanding performances in general. Pitchbook.com reported that about one-third of Series A venture funding went to accelerator-backed startups in 2015.[8] Consistent with my back-of-envelope calculation, participation in an accelerator becomes a check-box on the to-do list for startups.[9] [10]

Physically, accelerators are concentrated in the well-known technology startup hubs and major cities of San Francisco-Silicon Valley, Boston-Cambridge, and New York, which account for about 40 percent of all accelerators in the United States between 2005 and 2015. The other 60 percent spread across 35 states and the District of Columbia.

Most early accelerators focused on high-tech startups, aiming to generate a higher return and social impact. While it is still a focus for many programs, new accelerators are beginning to diverge into more industries and communities in recent years. Interestingly, despite significant heterogeneity in terms of concentrations and purposes, the majority, if not all, of accelerators follow the model of Y Combinator and TechStars closely in terms of seed investment, cohort-based three-month programs, and mentorship, although it is not clear

[7] Source: http://www.ianhathaway.org/blog/2016/3/1/startup-accelerators

[8] Source: https://pitchbook.com/news/articles/one-third-of-us-startups-that-raised-a-series-a-in-2015-went-through-an-accelerator

[9] Each year there are about 400,000 new firms registered in the U.S.. Around 10% of them, or 40,000, are medium to high tech startups (based on Kauffman Firm Survey). According to F6S.com (one of the biggest accelerator program network), the average acceptance rate of accelerators is about 4% in the U.S.. While successful applicants applied 3.3 times before being admitted, unsuccessful startups applied 1.8 times. To be conservative, assume each accelerator takes 20 startups per year (GUST 2015 reported 2,968 startups graduated from 111 accelerators in the U.S.), 170 accelerators across the country would receive applications from 30,000 unique startups per year.

[10] Source: https://alexiskold.net/2014/08/19/top-10-reasons-to-join-and-not-to-join-an-accelerator/

whether such features are the best fit. And unsurprisingly, there are significant variations in performances. As of 2016, YC had invested in about 940 companies, including some well-known unicorns such as Dropbox and Airbnb.[11] YC has a combined market capitalization of over 65 billion. About 170 YC graduate startups have been acquired with the estimated total value of over 3 billion. On the other hand, not all accelerators have matched YC's success. For example, neither South Carolina's NextStart nor Minnesota's Project Skyway lasted for more than two years. While NextStart closed quietly, Project Skyway reformed as Skyway Fund and started traditional angel investing after its second cohorts finished in 2012.

2.2.3 Accelerator Value Creations

Accelerators Create Value

Venture financing is an important source for startups to accumulate physical assets (see Da Rin et al. [45] for a survey). Human capital, defined more generally as "managerial capital" to represent "soft" capital such as management skills and business networks, is also critical for firm performance (e.g.,Bloom and van Reenen [25]). Industry insiders and researchers widely acknowledge that accelerators are helpful in both ways.

According to the surveys by Christiansen and Tech.eu, startups consider the managerial capital improvement from mentorship and networking among the most valuable assistance from accelerators.[12] [13] While the amount of seed investment receives the lowest importance rank in the surveys, the results are inconclusive for the importance of activities focusing on fundraising, which are critical for some startups but a distraction for others. Even accelerators themselves appear to disagree on how they create value. Many well-known programs,

[11] Dropbox is the first public firm which graduated from an accelerator as of April 2018.
[12] Source: https://www.seed-db.com.
[13] Source: http://tech.eu/features/815/what-startups-want-from-accelerators-research/.

like Y Combinator and TechStars, emphasize their brand names, outstanding mentors, and well-developed alumni network. They claim to focus on their graduates' long-term growth. Meanwhile, some programs try their best to improve on their graduates' chance to secure venture investment at or shortly after the "Demo Day."

Early research (see Tasic et al. [144] for a survey) provided qualitative evidence that accelerators' assistance in managerial capital is valuable for entrepreneurs. More recently, Gonzales-Uribe and Leatherbee [81] empirically demonstrate that managerial skill training improves startup performance. Hallen et al. [87] show evidence on the startup learning effect during accelerator programs. For financing, Kim [101] models accelerators as a form of certification for startup quality. Fehder and Hochberg [62] show that regions with some accelerators see an increase in seed and early-stage financing. Yu [151] finds that accelerator graduates obtain venture financing earlier than comparable non-accelerator-participants.

Economic Mechanisms of Accelerator Value Creations

For managerial capital improvement, the accelerator mechanism offers a platform to facilitate knowledge and resource sharing from experienced mentors/investors to startups. With economies of scale, this mechanism lowers the cost to gather experienced mentors, offer networking events, and provide valuable business support. Further, creating a community of people who share similar interests in the entrepreneurship world, the accelerator can generate long-lasting impact. The knowledge and experiences obtained in accelerators may substitute years of actual operation experiences and therefore accelerate the firm growth.

For financing, while the accelerator often provides some seed money, the amount is small and not considered significant financing for startups.[14] Instead, the accelerator's fixed-term cohort-based structure allows it to serve as an intermediary connecting startups and investors. It can reduce information asymmetry in the venture market with two advantages.

[14] Many market participants consider the seed as a stipend during the programs (Hallen et al. [87]).

First, dealing with a group of startups at the same time can improve screening with lower cost, as pointed out by Ramakrishnan and Thakor [131]; and second, by taking a small equity with some seed investment, accelerators send a credible signal to outside investors, following the argument in Breadley et al. [28]. The screening by accelerators is especially helpful for early-stage startups as they lack credible business quality signals to attract venture investors. Besides, working with startups for several months, many accelerators offer education to improve entrepreneurs' pitching skills and help them to network with potential investors, which are helpful to reveal information about the candidate's quality.

To evaluate the value creation channels, I focus on accelerators' direct impacts by studying the effects that are not caused by any other improvement. For example, the following three effects are indirect: the improved managerial capital by spending money on networking because the accelerator graduate obtained more venture investment; the better venture financing because the startup improved its operation from knowledge learned from an accelerator; and, the financing improvement in the long run caused by the financing improvement in the short run. A key argument of this project is that the improvement of startup financing around and shortly after graduation provides an upper bound for the accelerator's screening effect.[15]

For financing, the screening signal becomes irrelevant in the long run since there will be more reliable information on the startup quality, such as the production and sales record, revealed over time. For managerial capital, one possible way the screening can add value is through its impact on the firm's sales. This effect is ignorable because customers pay more attention to the product than the startup background. Another way is through attracting business partners, which should not be important in the long run either with a similar intuition as discussed before for the financing case. In the short run, while screening may

[15] This argument is similar to the one in Farber and Gibbons [61], which shows that schooling effect can be independent of human capital gain through experience but with decreasing impact on wages.

help startups find good business partners, it is also likely to be reflected in the short-term financing quality because the investors can notice such improvement. While the public expectation of the managerial capital improvement from screening can be different than the real value for the startup, the rational public expectation should be consistent with the average of the startup's actual values.[16]

The following (Figure 2.2) diagram illustrates the two value adding channels in a diagram of firm growth. The x-axis represents the firm value (e.g. net present value (NPV)) and the y-axis is time. Before a startup is ready for venture financing, it may take several years of slow growth to set up its team and product. Once it is ready for venture financing, the startup grows faster with help from venture capitalists. Such growth slows down again when the firm becomes more established. Most accelerator participants are firms at the edge of receiving their first venture financing.

The financing improvement through screening is a one-time inward shift of the firm development curve because the accelerator can help startups to enter the fast development zone earlier. The managerial capital improvement is represented as the increased slope of the value curve. This is because a startup with higher managerial capital can grow faster with the same amount of initial physical assets. While the financing improvement is effective immediately, the managerial capital improvement takes time to realize and sees its impact increase over time.

Different Implications of the Value Creation Channels

If the screening effect is critical for accelerator participants, too many such programs are a concern because screening (e.g., Stiglitz [140]) can generate a negative spillover effect as resources will be reallocated from those in worse condition to those in better condition.

[16] The screening may be able to affect factors of a startup's operation other than those mentioned here. However, the arguments for such impacts are similar.

Further, Riley [133] points out that too much screening increases social cost for signaling. In an extreme case, when most startups participate in some accelerators, we come back to the world without signaling but with the cost of running accelerators. Finally, we need to be careful about the kind of signal that is sent out from the selection mechanism. For example, holding a program which only serves a specific community may fall short of expectation because investors know that admittance by an such accelerator does not necessarily mean the startup has good business quality.

On the other hand, if the accelerator creates most value in the managerial capital, it is unclear that the format of those early accelerators fits every scenario. For example, the seed for equity model, which is helpful to send a credible signal as discussed before, may not be necessary for every program.[17] Further, too much focus on fundraising during "Demo Day" and training on pitching skills can be a distraction, generating more cost than benefit.

2.3 Two-Sided Matching Model and Three-Stage Estimation

I develop a three-stage approach to identify the relative importance of short-term financing in the total value creation of accelerators as an upper bound for the impact of screening.

With rational expectation, the first two stages generate a consistent measure for expected short-term financing quality using ex-post funding information within one year after graduation. Specifically, the first stage recovers the accelerator production function given observed covariates through the matching pattern. The second stage consistently estimates the accelerator's impact on firm financing with the first stage result. The measure is then calculated using the second stage estimates.

[17] Some programs, although few, start to charge their participants. e.g., https://pando.com/2013/04/25/this-accelerator-charges-its-companies-25000-thats-just-wrong-right/

In the third step, I examine the importance of short-term financing by studying how the variation in the proposed measure affects the accelerator admission process.

The two-sided matching model uses the same approach as in Chen [31]. I briefly introduce the model setup and estimation here and refer to his paper for detailed discussions.

2.3.1 Why a Matching Model

The accelerator admission is a match between the accelerator and startup. It is instructive to observe that each startup deliberates among many viable alternative accelerators, and each accelerator considers viable startups from their pool of applicants. Through the equilibrium channel, the values of possible alternative matches—both implicit and explicit applications—provide a bound for the value of each realized match. Formalizing this intuition, this paper analyzes the market participants' utility function with a revealed preference approach. I use the characteristics of each startup's and accelerator's alternative matches to estimate the value of the matches that do occur.

Competition exists on both sides of the accelerator market. Because accelerators have limited capacity, they only admit the best startups. At the same time, accelerators compete to attract good (desirable) candidates because each startup can only join one accelerator. By assuming that each agent's decision is independent and has no externalities, standard discrete choice models, such as Logit and Probit, cannot accommodate markets with two-sided selection and competition in the choice set (See Mindruta et al. [116] for a detailed discussion). To address this challenge, economists have developed two-sided matching models to capture this market structure explicitly.

I model the accelerator admission as a two-sided matching game (Roth and Sotomayor [135]). Each accelerator-startup match creates a joint match value, and the match value is split according to the pre-announced equity-share and seed investment, which are considered exogenous in this paper.[18] Agents from both sides of the market maximize payoffs by choosing matches with agents on the other side.[19] In equilibrium, agents have no feasible deviations to match with other partners and weakly increase the payoffs for all participants. In the estimation, I construct counterfactual matches to each pair of observed matches within the same market by switching their partners. Comparing pairs of observed matches with their counterfactual matches yields sets of inequalities required by the equilibrium condition. Given these inequalities and a parametric form for the match value function, I choose the parameter vector that maximizes the fraction of inequality sets that hold. This is the maximum score estimator I propose in this paper. Compared with similar estimators as in Fox [66] and Akkus et al. [6], this estimator studies non-transferable utility matching games, in which neither the uniqueness or the competitiveness of equilibrium is guaranteed.

2.3.2 First Stage: The Accelerator Production Function

During the accelerator admission process, I assume each startup has information on all accelerators on the market.[20] Also, accelerators and startups share a total matching surplus U_{as} for a given match between the accelerator a and the entrepreneur s.[21] Their expected utilities can be written in the following forms:

$$U_{as}^{s} = (1 - E_a) * U_{as} + t_a - c_{as}^{s}$$

$$U_{as}^{a} = E_a * U_{as} - t_a - c_{as}^{a}$$

[18] This is based on the fact such terms that are fixed once the accelerators announce them.

[19] To guarantee the existence of equilibrium, this paper abstracts away from potential gain from complementarity in the accelerator portfolio. It is difficult for the accelerator to make decisions based on the portfolio given a large number of applications. In reality, it is not rare to see two direct competitors in the same cohort (Stross [141]).

[20] Thanks to the popularity and public profile of accelerators, it is easy to find their programs online.

[21] The shared total surplus can be interpreted as the firm value at accelerator graduation. It does not necessary to exclude non-firm related utilities such as access to the accelerator network or having a high-quality entrepreneur as a mentor in the future. The key assumption here is that the utility is divided according to the equity share.

where E_a is the equity share of the accelerator a and t_a is the seed investment from the accelerator a, which are both exogenously given; c_{as}^s and c_{as}^a are individual costs, which are not captured by U_{as} nor the equity/seed, for a and s respectively in the given match. As mentioned before in Section 3.3, I consider the seed investment as a stipend for entrepreneurs that does not increase the firm value. This assumption is not important for the model identification and can be changed. One can ignore c_{as}^s if the startup faces the same individual costs for all possible accelerators.[22] A similar argument also applies to c_{as}^a.

A startup's individual cost includes the founders' time and living expenses during the accelerator program. It may also include migration spending if the startup needs to relocate. Since the majority of accelerator programs last for three months, the cost variation on time spending is small. Due to data limitation, I assume that costs of living are very similar across accelerators. The migration cost includes the firm's moving expenses and potential business loss. This cost can directly reduce the firm valuation and is therefore controlled by a relocation dummy in U_{as}. I assume accelerators face the same cost across all possible startup candidates.

Let the observed covariates of entrepreneurs be X_s, accelerator covariates be X_a, and their interactions be X_{as}. Let $X^{as} = \{X_s, X_a, X_{as}\}$. I impose the following functional form for U_{as}

$$U_{as} = X^{as}\beta + \varepsilon^{as}$$

where ε^{as} is assumed to follow distributions consistent with the median independence feature such that $Median(\varepsilon^{as}|X^{as}) = 0$.

Some additional model assumptions: 1) It is a static model in which all observables are exogenous; 2) Each year is a separate market.[23] Agents on one side of the market can only be matched with agents from the other side in the same market; 3) Some accelerators run

[22]Note that this does not require all startups to have the same cost.

[23]This assumption is made for convenience and does not affect the model result's consistency.

multiple programs in various locations across years. I model the matching between programs and startups; and 4) each program can admit multiple startups, but each startup can only join one program.

2.3.3 Second Stage: Accelerator's Impact on Startup Performance

The second stage studies the accelerator's impact on startup performance, especially on short-term financing. To address concerns with unobserved heterogeneity, I utilize the first stage results and a proxy of realized matching value.

Take the OLS, for example.[24] For a given startup performance measure, PF (e.g. funding probability), and the match between a and s, $PF_{as} = Z^{as}\delta + \varepsilon^{as}_{fund} = Z^{as}\delta + \gamma\varepsilon^{as} + e^{as}$, where Z^{as} is a vector of observed covariates, γ is the correlation between ε^{as} and ε^{as}_{fund}, and e^{as} is i.i.d. Given $\varepsilon^{as} = U_{as} - X^{as}\beta$ as in the first stage, we have $PF_{as} = Z^{as}\delta + \gamma(U_{as} - X^{as}\beta) + e^{as}$, which can be consistently estimated if one observes U_{as}. Inspired by Akkus et al. [5], I use a proxy P_{as} for U_{as} as $U_{as} = P_{as} + v_{as}$, where v_{as} is independent of P_{as}, Z^{as}, and X^{as}. In this way, $PF_{as} = Z^{as}\delta + \gamma(P_{as} - X^{as}\beta) + \xi_{as}$ with $\xi_{as} = (e^{as} + \gamma v_{as})$ and ξ_{as} is independent of P_{as}, Z^{as}, and X^{as}. In this project, I let P be the dummy of startup survival (either has been acquired or is in operation) status five years after graduation. Other alternatives and robustness checks will be discussed in the appendix.

In summary, the second stage estimation is:

$$PF_{as} = Z^{as}\delta + \gamma\left[P_{as} - (X^{as}\beta)\right] + \xi_{as}$$

2.3.4 Third Stage: Relative Importance

This stage estimates the matching model as in the first stage but with the financing measure calculated from the second stage result. Additional assumptions are imposed to obtain

[24] It is also applicable to other similar methods such as Logit and Probit.

consistent results. First, I assume the equity share E_a to be the same for all accelerators in the same market. Second, I assume ε^{as} is independent, identical, and symmetrically distributed. Third, I assume the accelerator graduation value is a linear combination of the startup original value (before accelerator) V^s and the value added by accelerator V^{as}. Further, V^{as} can be linearly decomposed to the value added in financing V_F^{as} and in managerial capital V_H^{as}.

For a given match (a, s), denote the measure for financing as f_{as} and measure for managerial capital as h_{as}. We have:

$$\begin{aligned} U_{as} &= V^s + V_F^{as} + V_H^{as} \\ &= V^s + w_f f_{as} + w_h h_{as} \end{aligned}$$

where w_f and w_h can be interpreted as relative weights of the two value creation channels.[25] To identify w_f without data on non-matched startups (non-accelerator participants), I decompose $V^s = \hat{V}^s + w_f f_s$, where f_s is the startup's original financing quality, so that $F_{as} = f_s + f_{as}$ is the total financing value at graduation. In this way, $U_{as} = \hat{V}^s + w_f F_{as} + w_h h_{as}$ and the weight of financing can be identified with a measure of F_{as}.

I use the agent's belief on the probability of obtaining venture financing within one year after graduation as a measure for F_{as}, denoted as FP_{as}.[26] In equilibrium, ex-ante beliefs about funding probability should be consistent with ex-post realized funding probability. I use observed funding information for each startup to form such beliefs based on second stage results. I define the short-term as one year after graduation, because it allows time

[25]Here I assume everyone has the same w_f and w_h. The model can be expanded to relax this assumption. However, in order to make sure both the first and third stage are correctly specified, one needs to include multiple interactions in the first stage model. This may significantly increase the data requirement and computation time.

[26]Here I assume higher probability is strictly preferred by everyone. This does not exclude those claiming that they do not need immediate funding because it is plausible to argue that everyone likes funding at a reasonable cost. The model allows such cost to be different across firms

for the negotiation on financing terms and the gap between funding decisions and actual investments. Note that such measure is a proxy for general funding quality. Alternatively, I can use the funding size as a measure, but it may introduce more noises as the information on equity share is mostly missing.

Ideally, I could calculate $FP_{as} = Z^{as}\delta + \gamma\left[P_{as} - (X^{as}\beta)\right]$ for each potential match. However, this is not possible, as I do not observe P_{as} for counterfactual matches. Instead, I create a consistent proxy, denoted as MF_{as}, for FP_{as}. Let $MF_{as} = Z^{as}\delta$, so that $FP_{as} = MF_{as} + \gamma\varepsilon^{as}$. I assume that any additional variables in Z^{as}, but not in X^{as}, to be independent with ε^{as}.

The relative importance of financing is likely to be non-linear. For example, a startup located in the midwest may care more about the marginal improvement to secure venture financing than a similar startup in Silicon Valley. To capture such curvature, I include the square term of the financing measure and write $w_f^{as}F_{as} = w_{f1}^{as}FP_{as} + w_{f2}^{as}(FP_{as})^2$. This indicates $w_f^{as}F_{as} = w_{f1}^{as}MF^{as} + w_{f2}^{as}(MF^{as})^2 + (w_{f1}^{as}\gamma\varepsilon^{as} + w_{f2}^{as}(\gamma\varepsilon^{as})^2 + w_{f2}^{as}(2\gamma\varepsilon^{as}MF^{as}))$. With the same equity share across accelerators, we can write $U_{as}^s = (1-E) * [w_{f1}^{as}MF^{as} + w_{f2}^{as}(MF^{as})^2 + X^{as}(\beta_v + \beta_h) + (w_{f1}^{as}\gamma\varepsilon^{as} + w_{f2}^{as}(\gamma\varepsilon^{as})^2 + w_{f2}^{as}(2\gamma\varepsilon^{as}MF^{as}))] - t_a$. Denote $\tau_{as} = w_{f2}^{as}(\gamma\varepsilon^{as})^2$, the deterministic utility as D_{as}, and $\varphi_{as} = w_{f1}^{as}\gamma\varepsilon^{as} + w_{f2}^{as}(2\gamma\varepsilon^{as}MF^{as})$. We have:

$$
\begin{aligned}
Pr(U_{as}^s > U_{a's}^s) \Leftrightarrow & \, Pr((1-E)(D_{as} - D_{a's}) > (1-E)(\varphi_{a's} - \varphi_{as} + \tau_{a's} - \tau_{as})) \\
\Leftrightarrow & \, Pr(D_{as} - D_{a's} > \varphi_{a's} - \varphi_{as} + \tau_{a's} - \tau_{as})
\end{aligned}
$$

It is straightforward to see that $MED(\varphi_{a's} - \varphi_{as} + \tau_{a's} - \tau_{as}) = 0$ and therefore $Pr(U_{as}^s > U_{a's}^s) > 50\%$ if and only if $D_{as} > D_{a's}$.

Let $\hat{V}^s = X^{as}\beta_v + \varepsilon_v^{as}$ and $w_h^{as}h^{as} = X^{as}\beta_h + \varepsilon_h^{as}$. Assume $\varepsilon_h^{as} + \varepsilon_v^{as}$ to be independent, identical, and symmetrically distributed with mean zero. I estimate the following function:

$$
\begin{aligned}
U_{as} &= \hat{V}^s + w_f F^{as} + w_h h^{as} \\
&= (X^{as}\beta_v + \varepsilon_v^{as}) + w_f F_{as} + (X^{as}\beta_h + \varepsilon_h^{as}) \\
&= (X^{as}\beta_v + \varepsilon_v^{as}) + [w_{f1}^{as} MF^{as} + w_{f2}^{as}(MF^{as})^2 + (w_{f1}^{as}\gamma\varepsilon^{as} + w_{f2}^{as}(\gamma\varepsilon^{as})^2 + w_{f2}^{as}(2\gamma\varepsilon^{as}MF^{as}))] + (X^{as}\beta_h + \\
&= w_{f1}^{as} MF^{as} + w_{f2}^{as}(MF^{as})^2 + X^{as}(\beta_v + \beta_h) + (\varphi_{as} + \tau_{as})
\end{aligned}
$$

Including the square term of the financing measure makes the model very costly to estimate because the number of controls increases exponentially. With limited data and computation power, I restrict the total number of controls in this model.

The identification of w_f^{as} requires an exclusive restriction variable which only contributes to the short-term financing in the accelerator production function. Assuming the macroeconomy condition impacts the matching value only through F_{as}, I use a dummy indicating whether it is before one year after the financial crisis.[27] I place the threshold at July 2010 instead of the official end of the great recession based on the NBER definition, because 1) According to PitchBook (Figure 2.3), while venture investment deals came back to the upward trend in 2009, the recovery only speeded up after the third quarter of 2010. This is especially true for the market of early startups, which is targeted by "Angel/Seed" and "Early VC." 2) The accelerator applications and admissions were decided at least several months ahead of the actual program. Graduates from 2009 programs are unlikely to be aware when the financing condition was going to get better during their applications.

Without information on firms which did not participate in accelerators, I provide an upper bound for $\frac{V_F^{as}}{V_H^{as}}$. This is not a concern because it only makes the project result more

[27] The biggest concern may be that there are more resources available for accelerators to improve their education quality after the crisis. Since accelerators attract applicants through public media channels, such improvement is unlikely to be confidential or only internally announced. However, I do not find any significant resource added to accelerators concentrated around the end of the financial crisis.

conservative. Let $\mathscr{A}$ denote the set for all possible a that can be matched with a given s. We know that V^s is upper bounded (the minimum value of $w_h H_{as}$ is bounded by zero) by the smallest $\overline{V^s} = (U_{a's} - w_f F_{a's}) + w_f f_s$ among all possible $a' \subseteq \mathscr{A}$. Therefore V_H^{as} is lower bounded by $\underline{V_H^{as}} = U_{as} - V_F^{as} - \overline{V^s} = (U_{as} - w_f F_{as}) + w_f f_s - \overline{V^s}$. Let $\hat{U}_{as} = U_{as} - w_f F_{as}$, then $\underline{V_H^{as}} = \hat{U}_{as} - \hat{U}_{a_{min}s}$, where $a_{min} = \underset{a \subseteq \mathscr{A}}{argmin}\{(U_{as} - w_f F_{as}) + w_f f_s\}$.[28] In practice, it is enough to calculate $\underline{V_H^{as}} = \underset{a' \subseteq \mathscr{A}}{max}(\hat{U}_{as} - \hat{U}_{a's})$. Further, V_F^{as} is upper bounded by $\overline{V_F^{as}} = w_f F_{as}$ when $f_s = 0$. We obtain $\overline{V_F^{as}}/\underline{V_H^{as}}$ as the upper bound for the ratio $\frac{V_F^{as}}{V_H^{as}}$ for any $a \neq a_{min}$.

2.3.5 Subsampling and Confidence Intervals

I follow Akkus et al. [6] to obtain subsampling and confidence intervals for the maximum score estimator. Normalizing the startup age to have parameter of $+1$ and -1 respectively, I estimate the matching models by running the differential evolution optimization routine from 40 different starting points (20 each for the positive and negative normalization, respectively) and selecting the coefficient vector that yields the highest value for the objective function. For valid inference, I generate the confidence intervals using the subsampling procedure described by Politis and Romano [129] and Delgado et al. [51] to approximate the sampling distribution. I randomly conduct 100 of these subsamples with sizes at about one third of the total data set.

For each of the subsamples, I estimate the parameter vector as for the whole dataset. Call the estimate from the sth subsample $\hat{\beta}_s$ and the estimate from the original full sample $\bar{\beta}$. The approximate sampling distribution for the parameter vector can be computed by calculating $\tilde{\beta}_s = (n_s/N)^{1/3}(\hat{\beta}_s - \bar{\beta}) + \bar{\beta}$ for each subsample, where N and n_s are the total sample size and given subsample size, respectively. I take the 2.5th percentile and the 97.5th percentile of this empirical sampling distribution to compute 95% confidence intervals for all of the estimates.

[28] The term $w_f f_s - \overline{V^s}$ cancels out in $\hat{U}_{as} - \hat{U}_{a_{min}s}$.

2.4 Data

2.4.1 Data Sources

I construct a novel dataset covering U.S. accelerators that existed from 2008 to 2011.[29] I study this time frame because the majority of currently well-known accelerators emerged during this period, and it allows me to collect ex-post startup performance up to five years. To have all accelerators maximize financial return, I exclude accelerators with different utility functions, such as those with restrictions on the community they serve and those that do not take any equity. These exclusions are unlikely to cause a significant impact as they only represent about 2% of the data. I also dropped startups with missing information on founder characteristics. Hereafter, I define a "program" as a cohort of accelerators. Some accelerators run multiple programs in various locations across years. In total, I identified 74 programs representing 27 accelerators and 776 startup graduates.

I use CrunchBase, AngelList, CapitalIQ, CBinsights, VentureXpert, and Linkedin to get the details of each program and its participants. Data on private firms often lack crucial information and may suffer a self-reporting bias since successful startups are more likely to release information to the public. To mitigate such concern, I cross check each firm by searching for related news and press releases. The bias of self-reporting is mild in this paper because I have found information even for failed startups, thanks to the publicity and popularity of accelerators.

Data on non-participants of accelerators is helpful to understand the value added by accelerators relative to other options. However, it is not necessary for this paper to generate consistent estimates (details in the model section). Since my focus is on whether founders' demographic characteristics affect their admission in accelerators, the non-participants data

[29] I collected data from 2005, the founding year of the first accelerator. I restricted attention to observations after 2008 as there were only two programs (Y Combinator and TechStars Boulder) before 2008.

does not contribute to my research question either.

To characterize accelerators, I collect information on their location, size, and terms offered (amount of seed investment and equity share). For each startup, I obtain its business age, location, founders' background (gender, education, and entrepreneurship experience), and operation (acquired, dead, or operating) and financing status.

To further capture some unobserved differences among accelerators, I categorize accelerators into three tiers and control the fixed effects of each. The first tier includes the two widely acknowledged "superstars" in this market - Y Combinator and TechStars. The second tier consists of all the accelerators who received ranks from the "Seed Accelerator Ranking Project" (SARP) except for the two in the first tier.[30] All the rest of the accelerators are in the third tier. While all Tier 1 and Tier 2 accelerators are still running, six of the Tier 3 accelerators stopped or joined other accelerators as a chapter. Note that I do not impose any restriction on the quality ranking across tiers, and the model estimates do not depend on the endogenously generated categorizing rule of tiers.

2.4.2 Summary Statistics

Table 2.1 shows a summary of programs and startups across accelerator tiers.

The accelerator participants are early-stage startups - mostly firms before any venture capital financing. Better accelerators, as indicated by the tiers, tend to take lower equity and

[30]SARP is led by Yael Hochberg and probably the only ranking conducted by economics researchers. Although the exact ranking criteria are unknown to the public, according to the website, "*The goal of our project is to provide greater transparency regarding the relative performance of programs along multiple dimensions that may be of importance to entrepreneurs. Many of the metrics in question, such as fundraising and valuations, are metrics accelerators and startups are reluctant to publicize out of concern for negative competitive effects should they become widely known to investors and competitors. As an independent, non-partisan research entity run by academics, we collect this sensitive data in confidence, distill it down, and provide information on the relative success of the programs and of the phenomenon as a whole – without revealing individual deal details. Our rankings are meant to provide guidance for entrepreneurs who are considering going through an accelerator, and who are wondering how they differ on performance across various categories.*" SARP has been running since 2013, and the rankings are available since 2015. See: seedranking.comcom

have bigger classes. A potential reason is that better programs have a lower cost of pulling resources to sponsor larger programs and create a higher total return. Additionally, Tier 1 accelerators take lower equities from startups but do not give the highest seed investment. The second tier programs are the most generous regarding startup valuation (calculated as seed/equity).

In my dataset, about 37% of the accelerator programs are found in startup hubs (CA, MA, NY). This pattern is similar to the geographic distribution of accelerators in 2015, in which about 40% of all accelerators in the U.S. were located in the well-known technology startup hubs and major cities of San Francisco-Silicon Valley, Boston-Cambridge, and New York.

The accelerator participants are significantly younger than non-participants. Azoulay et al. [12] reported that the average age of startup founders in the U.S. is 41.9. High-tech founders are a bit younger but still around 39 to 40, and this age range is not very different in startup hubs. If we interpret age as a proxy of general work experience, this indicates that accelerators' assistance may be a substitute for human capital accumulation over time. Further, while some consider accelerators to be designed for first-time entrepreneurs[31], I find one-third of accelerator participants have founded some company before. While not reported in the table, over 99% of entrepreneurs in my data have college degrees. About 35% of them also have graduate degrees, close to the figure of comparable non-participants during the same period (see appendix). The female participation rate, which is at 10% on average and below 5% in Tier 1, is low because 8%~16% of startups which received first venture funding during the same period are founded by women.[32]

Most early accelerators focus on high-tech startups, especially in the IT related fields, aiming to generate a higher return and social impact. While high-tech is still a focus, new ac-

[31] Source: https://alexiskold.net/2014/08/19/top-10-reasons-to-join-and-not-to-join-an-accelerator/

[32] Source: https://techcrunch.com/2018/01/15/the-portion-of-vc-backed-startups-founded-by-women-stays-stubbornly-stagnant/

celerators have recently diverged to work with different industries and communities. Despite heterogeneity in concentration and purpose, the majority of accelerators follow the framework of Y Combinator and TechStars. As of 2016, Y Combinator had invested in about 940 companies, including some well-known unicorns such as Dropbox and Airbnb.[33] Y Combinator has a combined market capitalization of over \$65b. About 170 Y Combinator graduate startups have been acquired with the estimated total value of over \$3b. However, not all accelerators have matched Y Combinator's success. For example, neither South Carolina's NextStart nor Minnesota's Project Skyway lasted for more than two years. While NextStart closed quietly, Project Skyway turned into the Skyway Fund and started traditional angel investing after its second cohort finished in 2012.

The first two rows of Table 2.2 show the five-year in operation rates, which is the percentage of graduates that are still in operation and have not yet been acquired, and the five-year exit rates, which is the percentage of graduates that have been acquired. Financing performance, including portions of startups which obtained venture financing within one year, five years, and 2-5 years after graduation, are reported in the last three rows. Tier 1 accelerators dominate in all the performance measures reported. Compared to those from Tier 3, graduates from Tier 2 accelerators enjoy better venture financing.

2.5 Results

2.5.1 Relative Importance of Screening

In this estimation, I excluded the 2011 summer cohort of Y Combinator since they received additional funding from the Star Fund. This leaves me with 648 firms. Due to data limitation and computation difficulty, I selected five variables in addition to the business age and the macroeconomy dummy to capture value variations.

[33] Dropbox is the only public firm which graduated from an accelerator as of April 2018.

The quality of young startups can heavily depend on the founding teams' quality. Experienced entrepreneurs have accumulated more managerial capital and financial assets to produce better businesses as discussed in the prior study (Gompers et al. [80], Hsu [93]) on serial entrepreneurs. Therefore the accelerator value added to a startup founded by such entrepreneurs may be systematically different from those founded by rookies. I include a dummy indicating whether at least one member of the founding team had founded some startup before. On the accelerator side, I include dummies of the accelerator tiers to capture quality differences. Additionally, I include the indicator of whether the accelerator and the startup are from the same state to control for the relocation cost. All interactions and square terms of the controls are also included in the matching value estimation of both the first and third steps.

The second step is a regression with a dependent variable as the indicator of whether the startup obtained venture financing within one year after graduation and the independent variables include all the first order terms of the first stage controls. The variable $(Proxy - MatchingValue)$ is the term $P_{as} - (X^{as}\beta)$ as in the model section.

Model Results

Table 2.3 reports the key results of the first and third steps. The results are normalized to +1 of startup age because it generates a higher matching score. The second stage results are in Table 2.4.

First of all, the amount of seed investment only has a marginal impact during the accelerator admission. The significant and positive coefficient of $(Proxy - MatchingValue)$ in the second stage indicates the sorting effect in the unobservable matching quality is important and better accelerators admit better startups. In Table 2.4, the year dummy pattern supports the argument that the venture investment market recovers since July 2010.

Serial entrepreneurs do not see much difference from rookies in terms of value creation in accelerators. This result is consistent with the opinion of Alex Iskold, Managing Director of TechStars NYC, that accelerators are not only for first-time entrepreneurs.[34] Further, serial entrepreneurs do not enjoy higher short-term financing rates after graduation either. Considering that experienced entrepreneurs tend to produce better startups and attract more venture investors, this finding suggests that the accelerator mechanism can reduce the differences between the veteran and rookie. Older businesses still enjoy higher funding rates but only in the short term, indicating that screening cannot replace the operation record as a quality signal to attract investors.

The accelerator tier dummies in the third stage capture the difference in the managerial quality improvements. The second and third stage results suggest that better programs both enjoy higher short-term funding probability and generate better mentorship quality for long-term growth. It is worth noting that the difference between Tier 1 and 2 programs increases in the last stage result compared with the one in the first stage. This finding is consistent with the top programs' claim that they focus more on the startup's managerial capital improvement for long-term growth. On the other hand, the difference between Tier 2 and 3 programs decreases. In fact, the Tier 2 dummy is close to an insignificant level in the third stage. This is not surprising as anecdotal evidence indicates that some Tier 2 programs tend to create more value in short-term financing improvement. The difference between Tier 1 and 2 programs decreases during the financial crisis as reported by the interactions of tiers and macroeconomy condition in first stage results. This pattern suggests the concavity of short-term financing importance.

Screening v.s. Managerial Capital

Following method provided in Section 2.3.4, I calculate the upper bound of the "Financing to Managerial Capital Ratio" of each firm except those being matched with their worst choices.

[34] Source: https://alexiskold.net/2014/08/19/top-10-reasons-to-join-and-not-to-join-an-accelerator/.

In total, I obtained 618 ratios.

Table 2.5 reports the summary statistics of ratios across different tiers of accelerators. The improvement of short-term financing is not very important in accelerator value creation since all ratios are much smaller than one, with the lowest value being only 0.23%. The relative importance of the screening effect is therefore even lower. This result is supported by the recent trend that more startups, which have already secured millions of venture investment, join accelerators. This is especially true for the top programs, who have much lower ratios compared with the other tiers. The results for Tier 2 programs are divided. While some of them, about 40%, follow the two top accelerators and have similar ratio levels, some others, about 30%, emphasize on short-term financing and have the highest ratio among all programs at about 30%.

Figure 2.4 shows ratio averages across states. Startup hubs - California, Massachusetts and New York - have lower ratios. This pattern still holds even when I removed Tier 1 accelerators in those states. A plausible explanation is that startups in these states have better venture financing opportunities without accelerators.

2.6 Conclusion

Separately identifying the screening effect from the human capital improvement attracts much attention in labor economics, especially in education studies, because these two channels have different social welfare implications. In this project, I estimated an upper bound of the screening effect in the accelerator market based on some specific industry features. I find that the accelerator mechanism helps startups mostly through its mentorship and business support, despite the fact that the screening pattern is also apparent. Such finding is especially true for the oldest, and arguably the best, two accelerators - Y Combinator and TechStars. The importance of screening increases when startups are facing a high cost to raise funds in alternative channels.

Table 2.1: Accelerator Profiles Across Tiers

Note: The accelerator participants are early-stage startups - mostly firms before any venture capital financing. The majority of these early accelerators focuses on high-tech startups, especially in information technology related fields. Better accelerators, as indicated by the tiers, tend to take lower equity and have bigger classes. Furthermore, the best accelerators take low equities from firms but do not give the highest seed investment. The second tier programs are the most generous in terms of firm valuation, taking low equity and giving high seeds. On average, the entrepreneurs who participate in accelerators are significantly younger than the non-participants (close to 40). Further, while some argue accelerators are for first-time entrepreneurs, one-third of participants have founded some company before.

	Tier 1	**Tier 2**	**Tier 3**
# of Accelerators	2	8	17
# of Programs	19	25	30
# of States Represented	5	6	15
# of Programs in Startup Hubs (CA, NY, MA)	13	8	6
Equity Range	5%~6%	5%~8%	5%~10%
Seed Investment Range	10k~20k	10k~50k	6k~25k
Average Valuation (Seed/Equity)	307.9k	364.2k	274.9k
Average Cohort Size	26.72	13.12	8.01
# of Startups	335	239	202
Startup Average Age	1.83	1.73	1.77
Average Founder Age	27.81	29.37	29.68
Inexperienced Team	61.49%	63.18%	61.39%
Female Founder in Team	4.78%	13.81%	9.90%
Graduate Degree Founder in Team	30.45%	39.75%	36.63%
Industry: IT/Software	46.27%	44.77%	52.48%
Industry: Social Media/Social Platform	16.71%	18.83%	19.31%
Industry: Healthcare/Education	4.78%	9.21%	7.43%
Industry: Others	32.24%	27.19%	20.78%

Table 2.2: Accelerator Performance Across Tiers

Note: "In Operation Rates" represents the percentage of firms still in operation and not acquired five years after graduation. "Acquisition Rates" represents the percentage of firms that have been acquired within five years after graduation. "One-Year" and "Five-Year" show the startup performance within one year and five years after graduation, respectively.

	Tier 1		Tier 2		Tier 3	
	Mean	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
Startup Operation Status (Five Year)						
In Operation Rates	49.25%	2.73%	58.16%	3.19%	47.52%	3.51%
Acquisition Rates	28.36%	2.46%	20.50%	2.61%	13.36%	2.39%
Startup Funding Rates						
One-Year	52.24%	2.73%	47.28%	3.23%	25.74%	3.08%
Five-Year	58.21%	2.69%	53.97%	3.22%	32.67%	3.30%
Startup Funding Sizes Given Funded (k$)						
One-Year	1,696	2,216	956	1,432	986	1,272
Five-Year	16,135	59,890	5,549	13,147	6,802	18,104

Table 2.3: Main Model Results: 1st & 3rd Steps

Note: ** indicates within 95% CI. This table reports results for the first and third stages of model estimation. Both of these two stages use a two-side matching maximum score estimator. "Crisis & One Year Aft Crisis" equals to one if the accelerator program happens before July 2010, which is one year after the official end of the great recession of NBER definition. "ST Funding Prob" is the calculated measure for short-term financing probability based on the method described in the model section (Step 2). Normalizing the startup age to have parameter of ± 1, I estimate the matching models (first and third stages) by running the differential evolution optimization routine from 40 different starting points (20 each for the positive and negative normalization respectively) and selecting the coefficient vector that yields the highest value for the objective function. For valid inference, I generate the confidence intervals using the subsampling procedure described by Politis and Romano [129] and Delgado et al. [51] to approximate the sampling distribution. I randomly conduct 100 of these subsamples with sizes at about one third of the total data set. For each of the subsamples, I estimate the parameter vector as for the whole dataset. Call the estimate from the sth subsample $\hat{\beta}_s$ and the estimate from the original full sample β. The approximate sampling distribution for the parameter vector can be computed by calculating $\tilde{\beta}_s = (n/N)^{1/3}(\hat{\beta}_s - \beta) + \beta$ for each subsample, where N and n_s are the total sample size and given subsample size respectively. I take the 2.5th percentile and the 97.5th percentile of this empirical sampling distribution to compute 95% confidence intervals for all of the estimates.

	1st Step			3rd Step		
Variables	**Coef**	**C.I. (95%)**		**Coef**	**C.I. (95%)**	
Experienced	-1.99	-6.78	1.36	-2.34**	-5.05	-0.41
Tier 1 Accelerator	9.67**	7.73	26.09	16.21**	10.38	20.24
Tier 2 Accelerator	6.75**	3.06	18.75	2.90**	0.42	6.65
Out-of-State Participant	-5.70	-7.05	2.67	-16.48**	-18.99	-8.32
Crisis & One Yr Aft Crisis	-6.58**	-11.37	-0.16			
Crisis & One Yr Aft Crisis*Exp	1.97**	1.42	5.507			
Crisis & One Yr Aft Crisis*Startup Age	2.42**	2.42	7.375			
Crisis & One Yr Aft Crisis*Tier 1	17.91**	1.25	22.76			
Crisis & One Yr Aft Crisis*Tier 2	20.38**	2.73	23.53			
Crisis & One Yr Aft Crisis*Out-of-State Participant	-1.11**	-19.42	-1.11			
Seed	0.80**	0.315	1.16	0.15**	0.15	30.48
Constant	49.57**	48.77	56.14	57.63**	55.28	68.57
ST Funding Prob				73.36**	59.92	74.15
(ST Funding Prob)^2				-110.41**	-110.55	-87.65
Startup Age	1	super consistent		1	super consistent	
Squared Terms and Other Interactions[35]		Y			Y	
Matching Score/Max Score		81.94%			82.55%	

[35] **For dummy variables, one cannot separately identify the parameters of first and second orders.**

Table 2.4: Main Model Results: 2nd Step

Note: The stars indicate significance level (* for 90%, ** for 95%, and *** for 99%). "Crisis & One Year Aft Crisis" equals to one if the accelerator program happens before July 2010, which is one year after the official end of the great recession of NBER definition. This table shows the regression results of the second stage estimation described in the model section. All three models reported here have the independent variable of indicators on whether the startup obtained venture financing within one year after graduation. Model 1 does not control for each individual year fixed effects. Model 2 does not control for the financial crisis fixed effects. Model 3 controls for both year and financial crisis fixed effects.

Variables	**Model 1**		**Model 2**		**Model 3**	
	Coef	**Std. Err.**	**Coef**	**Std. Err.**	**Coef**	**Std. Err.**
(Proxy-Matching Value)	0.34***	0.03	0.35***	0.04	0.34***	0.04
Experienced Founder(s)	0.04	0.03	0.02	0.04	0.02	0.04
Startup Age	0.06***	0.02	0.05***	0.02	0.06***	0.02
Tier 1 Accelerator	0.22***	0.04	0.25***	0.05	0.26***	0.05
Tier 2 Accelerator	0.18***	0.04	0.18***	0.04	0.18***	0.04
Out-of-State Participant	-0.11***	0.04	-0.11***	0.04	-0.11***	0.04
Crisis & One Yr Aft Crisis	-0.13***	0.04			-0.12*	0.07
Yr 2008			-0.19***	0.06	-0.07	0.09
Yr 2009			-0.16***	0.05	-0.04	0.09
Yr 2010			-0.11**	0.04	-0.07	0.05
Constant	0.22***	0.05	0.27***	0.06	0.26***	0.06
Observations	648		648		648	

Table 2.5: Upper Bound of F/H ratios across Accelerator Tiers

Note: This table reports some statistics of the calculated ratios of the relative importance of the short-term financing to other value created by accelerators.

	Tier 1	**Tier 2**	**Tier 3**
Mean Ratio	10.55%	21.11%	21.96%
Min Ratio	0.23%	3.09%	8.54%
Max Ratio	16.92%	38.99%	36.86%
Standard Deviation	4.36%	10.88%	6.17%

Figure 2.1: Accelerator Process

This figure shows the flowchart of the accelerator process. The whole procedure of accelerators starts with a public announcement of the details and terms of the program, such as application requirements, resources provided, seed investment, equity share, class size, location, and schedule. Once announced, these terms stay the same for all participants. Entrepreneurs submit their applications as individual firms. Admitted entrepreneurs start the program together at the same time and in the same location. The program lasts for a fixed period, often three months, during which accelerators offer mentorship, network opportunities, and other forms of business support. At the end of the program, accelerators hold a “Demo Day” in which each startup pitches to a group of potential investors. Firms are officially off the hook in terms of participating in the accelerator after graduation, but they can, and often do, become involved in the alumni community.

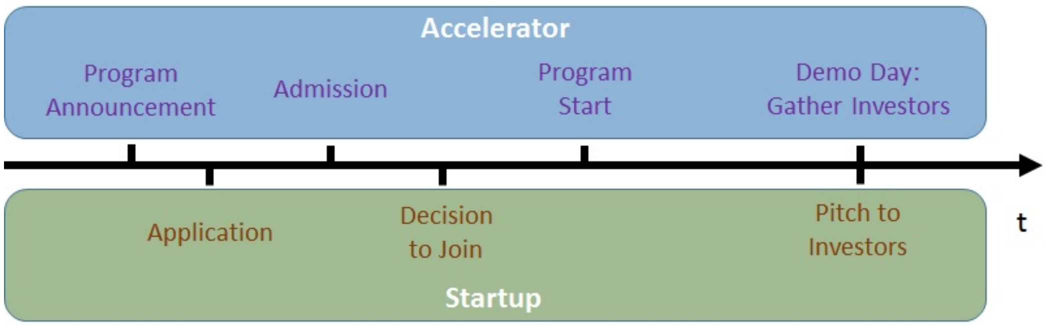


Figure 2.2: Accelerator Value Creation

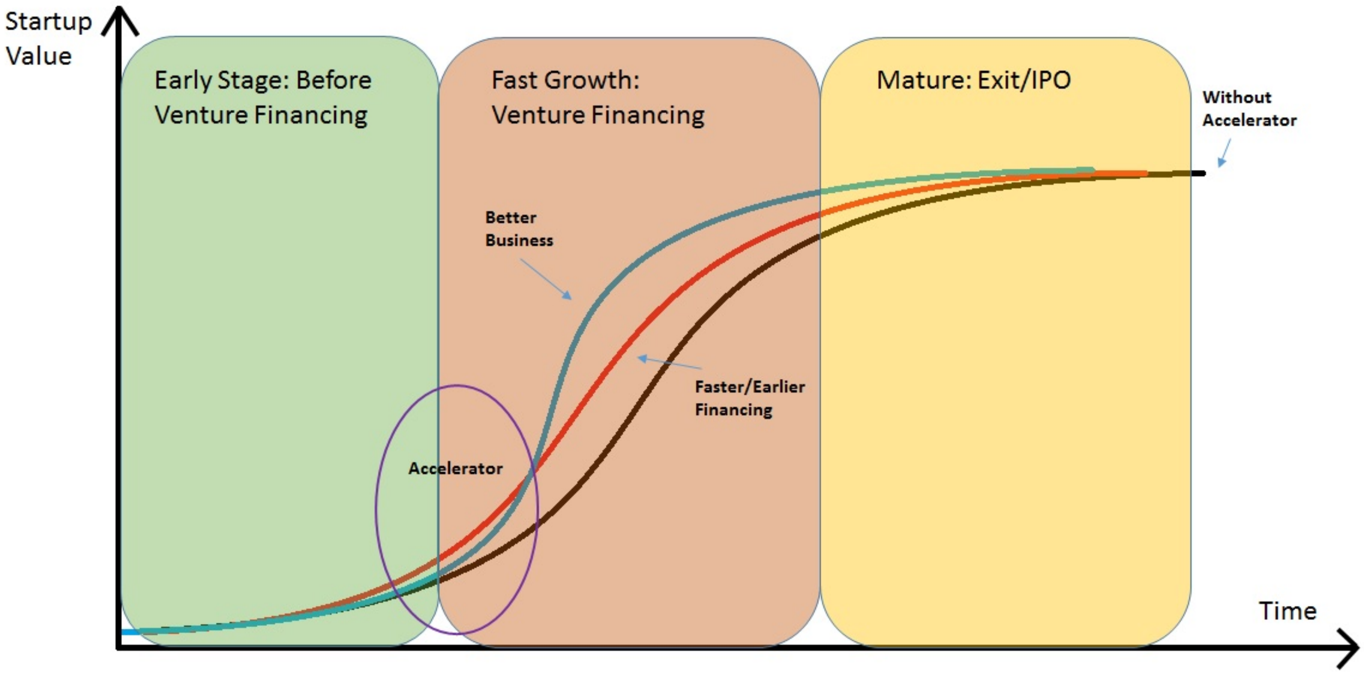


Figure 2.3: PitchBook Data on Venture Financing Deals

This diagram (source: pitchbook.com) shows venture financing trends over the past decade in the U.S. While venture investment deals reverted to the upward trend in 2009, the recovery only began to speed up after the third quarter of 2010. This is especially true of the market for early startups, which is indicated by "Angel/Seed" and "Early VC."

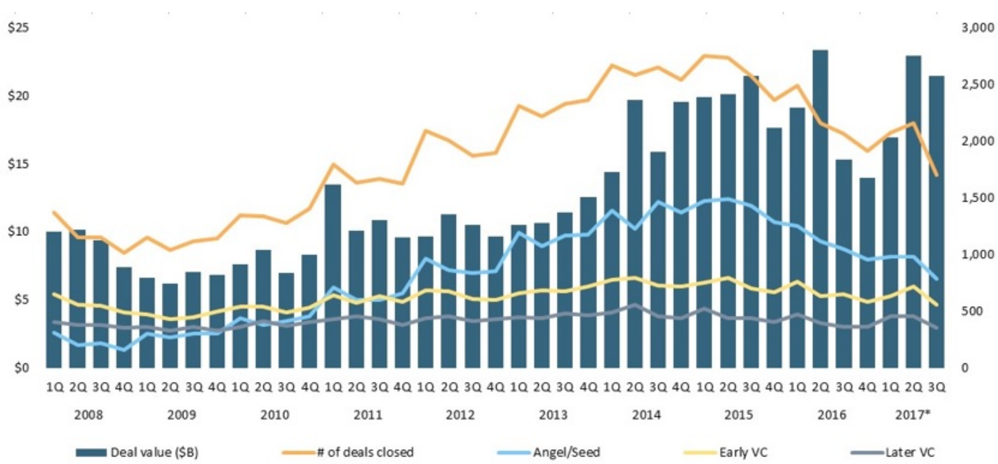
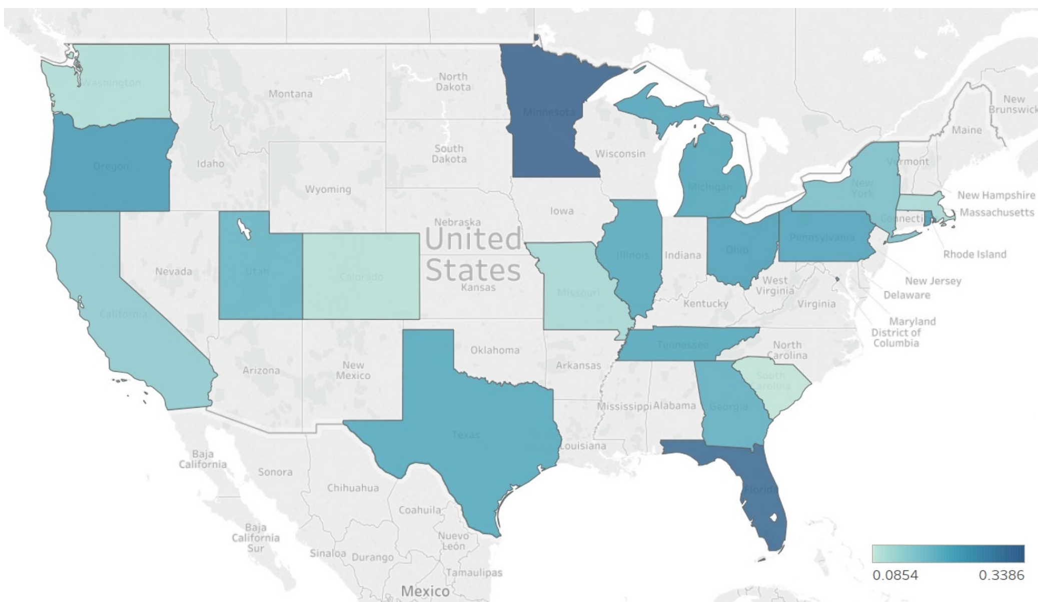


Figure 2.4: Average Upper Bounds of F/H Ratio Across States

This diagram shows the average upper bounds of the financing to managerial capital ratio across states.



Chapter 3

Not only who but where : A structural approach of incorporating location into our understanding of the audit market

This paper investigates the effects of auditor office location on client and auditor surplus. Using a two-sided matching market model, we find that, while both clients and auditors bear the costs of geographic distance, auditors disproportionately bear costs. Although distance exerts costs on clients, clients incur distance costs to gain auditor expertise. Next, we examine how the stickiness of audit office locations affects equilibrium audit market matches. The immobility of audit office locations results in a market-wide surplus loss of 1.6%, and leaves 8% of clients worse off. In addition, by aggregating individual client-auditor surplus at the MSA and state level, We find that in underserved regions, clients are more likely to choose their second-best auditors, and auditors are more likely to extract rents from clients. Finally, relocating audit offices in overserved regions, such as Detroit and Cincinnati, to underserved regions, such as Austin and Houston, improves market-wide surplus, and therefore, leaves clients and auditors in both regions better off. Overall, this paper contributes to the literature by highlighting how an audit market friction (stickiness in audit office location) affects surplus and auditor matches. This paper is a joint work with Seongjin Ahn

3.1 Introduction

An extensive literature in the industrial organization field suggests that an analysis of the effects of competition should incorporate both the number of firms in the same product market and the locations of firms relative to their customers Gabszewicz and Thisse [71], Porter [130], Tirole [145]. In the audit market, location affects audit quality as well as audit costs and fees. For example, assessing internal controls and providing feedback on information systems require auditors to observe these systems Office [124]. Because audit offices and expertise are dispersed and costly to move, distance constitutes a friction that potentially limits client access to pertinent expertise. However, these negative effects may be curbed by the fact that auditors have incentives to shift resources to valued clients. In this paper, we investigate the effect of auditor locations on the value clients and auditors get from receiving and providing an audit, to understand the distance-related friction.[1]

Two challenges exist in documenting the impact of the auditor's location on clients' and auditors' welfare and, consequently, the audit market as a whole. First, the value clients receive from an auditor and the costs incurred by the auditor are unobserved. Second, the value, costs, and audit fees are jointly determined with other market forces (e.g., competition). We address these challenges by developing an empirical client-auditor matching market model, based on the structure of multi-dimensional two-sided matching market models (e.g.,

[1] We define the value that clients get from auditors as client surplus and the value that auditors get from clients as auditor surplus. Client surplus is calculated as unobserved audit benefits less audit fees, following Gerakos and Syverson [75], Guo et al. [85]. Though our conceptual definition is identical to theirs, our estimation approaches differ. Auditor surplus is calculated as audit fees less unobserved audit costs, a new development in the literature. Total surplus is calculated as the sum of client surplus and auditor surplus. See Section 4 for more detail.

Fox [65]).

Two-sided matching market models have several advantages in an audit market setting. First, such a model separates the client-side decision and the auditor-side decision which jointly determines observed client-auditor pairs. This allows us to understand whether the client or auditor drives more or fewer audits (Donovon et al. [52]).[2] Second, the model – through the equilibrium concepts embedded in it – accounts for the dynamics of client-auditor selection contingent on other competitors in the market. In other words, equilibrium matches are formed only when neither clients nor auditors deviate from their matched pairs. Third, this model incorporates outside opportunities for which a particular client or auditor could feasibly be matched but were not. Hence, the model estimates how much value the client and auditor could have received under these alternative matches; this allows us to identify whether observed client-auditor pairs are suboptimal and to quantify the unobserved loss of surplus in the audit market, i.e., friction. Lastly, the counter-factual analysis enables us to understand under what circumstances friction in specific local audit markets can be resolved.

We first examine who (the client, auditor, or both) bears the costs of a greater distance between the auditor and client and how much. Our results suggest that, on average, a shorter distance between the client's headquarter and the auditor's office generates benefits for both the client and auditor; these benefits are higher for the latter. For instance, a 100-mile reduction in the distance between the client and auditor results in a $43 million increase in client surplus and a $64 million increase in auditor surplus, which is about 2.2% of total audit fees in 2015. The sensitivity of client surplus to client-auditor distance varies based on client characteristics. For example, bigger clients prefer auditors that are closer, but clients with better corporate governance associated with auditing benefit more from auditors that are farther away. In contrast, the sensitivity of auditor surplus to the distance is less dependent

[2] Appendix A. explains the erroneous inferences we may obtain if we model client-auditor selection as a one-sided market rather than a two-sided market. Appendix B. explains why reduced-form estimation hinders the understanding of whether the client or the auditor is driving results.

on client characteristics.

Next, we examine the economic significance of changes in distance to other characteristics. This analysis sheds light on the relative importance of client-auditor proximity, identifying the circumstances under which clients sacrifice other desirable auditor characteristics for higher proximity. We find that a one-standard deviation increase in distance is associated with a 3.04% decrease in client surplus relative to its mean. Distance has a larger effect on surplus than either industry expertise or Big N; a one-standard deviation decrease in these variables decreases client surplus by 0.2% or 2.07% relative to its mean, respectively. However, distance is substantially less important than the length of the client-auditor relationship; a one-standard deviation shift in relationship tenure leads to a 23.4% change in client surplus relative to its mean. We also examine the market-wide loss of total surplus due to the immobility of audit office locations. We do this by comparing the total surplus of new predicted equilibrium client-auditor pairs to the total surplus of actual equilibrium client-auditor pairs in a scenario where auditor location does not matter. This analysis is equivalent to examining whether auditor pairs would change if potential alternative auditors were located in the same location as a client's actual auditors. The results suggest that the market-wide total surplus might improve by 1.6%, and that approximately 8% of clients would be better off if the alternative auditors were located in the same locations as their actual paired auditors.

Additionally, we aggregate client and auditor surplus at the metropolitan statistical area (MSA) level and at the state level to examine the variation in market-wide total surplus and equilibrium audit price across the U.S. In underserved audit markets, where clients have relatively fewer auditor options in their geographical area, market-wide total surplus is lower and auditors charge higher audit fees relative to audit costs. This indicates that auditors have more bargaining power likely due to lower competition. Also, clients in underserved markets are 2.5 times less likely to select their first-best auditor compared to clients in overserved markets. Lastly, our results suggest that relocating or opening an audit office can increase market-wide total surplus in local audit markets with low market-wide total surplus. For example, relocating audit offices from overserved MSA to underserved MSA increases total surplus in both MSAs. At the state level, in California, where state-level total surplus is low, new auditor offices can increase market-wide total surplus by as much as 2.6%, depending on auditor characteristics.[3]

This study adds to the literature on the roles of distance in various settings. In non-audit settings, prior studies document the benefits of proximity obtained by facilitating monitoring and access to information. Mutual fund managers are more likely to hold shares of local firms and earn significant abnormal returns (e.g., Coval and Moskowitz [43, 44]). Banks located closer to their borrowers are more likely to lend to informationally difficult borrowers (e.g., Petersen and Rajan [127], Mian [115], Sufi [142]). Analysts who are geographically proximate to firms they follow are more accurate than other analysts (e.g., Malloy [109], Bae et al. [15]). Co-location of firms in the same industry reduces analysts' information acquisition costs (Jennings et al. [94]). Headquarters' proximity to plants increases plant level-investment and productivity (Giroud [77]). In audit-setting, prior studies document that more distant auditor selections are associated with low quality audits (Choi et al. [36], Jensen et al. [95]). My paper complements prior studies by documenting the costs associated with auditors' geographic proximity to clients.

This study provides new insights for regulators by highlighting how an audit market friction (stickiness in audit office location) affects audit market participants' surplus and auditor matches. The evidence that distance reduces surplus for both clients and auditors gives insights into why auditors maintain multiple audit offices and locate these offices close to their client pools. Additionally, our results suggest that clients in underserved markets

[3]Our model does not consider set-up costs associated office relocation or openings. Therefore, considering those initial set-up costs will reduce the amount of total surplus changes documented in this paper.

are less able to hire their “ideal” auditor than clients in other local audit markets. Moreover, auditors in those markets enjoy bargaining power and extract rents from clients by charging relatively high prices. Overall, this study provides evidence of market imperfections and suggests how they may be resolved.

Finally, this study overcomes some of the limitations of conventional approaches (i.e., OLS, probit model, logit model) that have been used to examine client/auditor selection and audit pricing. First, the method used in this paper allows the client-side and auditor-side decisions to be modeled separately. Prior studies typically model a single side of the selection process, as if the matching process between the auditor and client were similar to selecting and purchasing a soda at a convenience store. Omitting the market forces from one side in a two-sided market could provide an inaccurate picture of how the selection process occurs (e.g., Gale and Shapley [72], Becker [20], Roth and Sotomayor [135]). Second, the estimation approach in this paper overcomes self-selection issues (e.g., Francis [68], Hay et al. [88], Lennox et al. [105], DeFond and Zhang [49], Donovon et al. [52]). Third, unlike the conventional approach, this study does not assume that a client chooses auditors independently from and unconstrained by other clients (Hay et al. [88], DeFond and Zhang [49]). Prior studies argue that such an assumption leads to biased estimation and generates mixed results (e.g., Hay et al. [88]). We overcome these limitations by utilizing two-sided matching models that explicitly deal with these issues both theoretically and empirically.

3.2 Prior Research and Hypothesis Development

3.2.1 Spatial Competition and Audit Market Structure

Prior studies on theoretical models in spatial competition introduce firm location as a source of market power and an important differentiating factor between goods produced in the market (Biscaia and Mota [24]). Spatial economics focuses on economic agents’ location choices, e.g., given the location of one firm, which location should another firm select to maximize its profits (Hotelling [91])? The optimal location could be derived, for instance, by geographically mapping customer density and locating production to minimize transportation costs (Keune et al. [100]). Therefore, the ultimate concern of spatial economics is "the location of economic activity and the allocation of scarce and indivisible resources over space" (Duranton [55]).

Because the economic activities in the audit market, i.e., purchasing and providing audit services, involve space and location issues, prior studies of audit market concentration and industry specialization adopt theoretical arguments from spatial economics. Mayhew and Wilkins [113] document that industry specialist auditors, defined as industry experts with significantly higher market share than their competitors, earn higher audit fees. Numan and Willekens [122] define audit markets by industry segments per U.S. Metropolitan Statistical Area (MSA) and document a positive association between audit fees and industry specialist auditors in the local audit market. While Numan and Willekens [122] focus on Big 4 auditors, Bills and Stephens [23] and Keune et al. [100] include non-Big 4 auditors, and document the effect of non-Big4 market leadership on audit fees on both groups of auditors.

While this paper also examines the structure of the audit market from the angle of spatial competition, it differs from prior studies in two major ways. First, we focus on the effect of "physical" location rather than "product-space" location. For example, Numan and Willekens [122] define spatial competition in the following way: an auditor's relative market position in the audit market as the distance (in terms of industry market share) between the incumbent auditor and its closest competitor. We consider the impact of physical client headquarter location and office-level auditor location in local audit markets. Second, we focus on the economic wealth generated for client and auditor pairs as well as relative audit prices (based on audit benefits and audit costs), rather than studying absolute audit prices. This allows us to make welfare inferences about the audit market and determine whether auditors extract economic rents from clients due to their market power. Merely examining absolute audit fees does not allow researchers to make welfare inferences: since fees are transfers between clients and auditors, they are netted out in the market as whole.

3.2.2 Audit Market Competition

There is an ongoing debate about whether audit market concentration generates problems in the audit market and, if so, what the extent these problems is (Newton et al. [119]). On one hand, audit market concentration can be problematic because auditors in highly concentrated markets may provide low-quality audits and charge high fee premiums for rent-seeking purposes. Various government-issued reports raises these concerns. In the U.S., the government-mandated studies conducted by the U.S. Government Accountability Office (Office [123, 124]) document that audit market concentration may threaten audit quality because the Big N's market dominance may reduce competition, fostering entrenchment and thereby lowering auditor incentives to provide high-quality audits. In the European Union, regulators have expressed concerns about a high level of market concentration restricting companies' auditor choices and causing market disruptions if one of the Big 4 audit firms fails (Commission [40]). Prior studies document evidence of audit market concentration impairing audit quality as captured by increased earnings management and lower accrual quality (Boone et al. [26], Lennox et al. [105]).

On the other hand, there is evidence suggesting that audit market concentration may not be problematic. For instance, audit quality may improve as threats from client importance decline and clients have fewer opportunities to shop for opinions (DeFond and Zhang [49]). Some studies document that Big 4 concentration improves audit quality, as measured by fewer restatements and increased earnings quality (Newton et al. [119]). The Office [124] report points out that oligopolic competition can be intense. Also, the auditors with the highest market shares tend to do better-quality work (DeFond and Zhang [49]).

3.2.3 Mechanisms of Audit Market Friction

There are two possibilities how the distance between clients' headquarters and auditors' offices may lead to loss of value in the audit market. First, clients' "ideal" auditors may not be located close by. Prior studies suggest that audit services are a differentiated product, meaning that different clients place different values on various auditor characteristics (e.g., Gerakos and Syverson [75], Guedhami et al. [84], Copley and Douthett Jr [42], Fields et al. [63], Dechow et al. [47], Zimmerman [152]). It would be thus ideal for each client to engage its ideal auditor based on its preference function, and each auditor to provide service to its preferred client in a similar manner. Whether clients do actually have the opportunity to work with their first-choice auditors and vice versa is an empirical question. As spatial economics and mechanism design studies in the matching market suggest, markets where the economic goods being traded are indivisible and scarce may not obtain efficiency from a social welfare perspective, i.e., goods may not be allocated to the economic agents who need them most (Roth [134]).

For example, suppose a client is receiving audit services from a particular auditor who is located 50 miles away from the client's headquarters and has a medium level of industry expertise. This auditor might be the optimal choice based on the clients' preferences and auditor availability. However, the client might prefer to engage an auditor with higher industry expertise, even if such an auditor is located further away. From the client's perspective, the benefits stemming from industry expertise may justify the costs associated with additional distance. If such an auditor does not exist in the area, the client must settle for the second-best choice.

Second, friction in the audit market stem from the failure of the supply of audit services to keep up with shifts in demand. As local economic conditions change, client pools may grow in some regions and decline in others. If there is a time lag between these shifts in demand and auditor office openings and closures, we might expect to see market friction, i.e., extra costs for clients in regions characterized by shortages of audit services.

3.2.4 Client-Side Trade-Offs

As we alluded in prior section, the extent of friction in the audit market is based on audit market participants' valuation of their counterparts – namely, clients' valuation of different clients. From a client's perspective, audit benefits vary across auditors due to (i) heterogeneity in auditor attributes and (ii) heterogeneity in the value the clients place on those heterogeneous auditor attributes.

Prior studies provide evidence that companies reap capital market benefits from better-quality auditors (defined as industry expert auditors or Big N auditors).[4] Pittman and Fortin [128] document a positive association between ERC and auditor quality. Better quality auditors are also associated with higher analyst forecast accuracy, higher disclosure quality, and lower likelihood of future restatements (Behn et al. [21], DeFond and Zhang [48]). This evidence suggests that variation in auditor quality generates variation in audit benefits for clients.

Audit benefits vary based on not only auditor-side characteristics but also client-side characteristics. Politically connected clients are more likely to choose Big N auditors (Guedhami et al. [84]), which enables them to obtain higher financial statement transparency and to get cheaper equity financing. Clients are more likely to choose auditors whose incumbent clients have high financial statement similarity (Brown and Knechel [29]). Copley and Douthett Jr [42] document that clients that are difficult to value are more likely to switch to Big N auditors before they file for IPOs. Gerakos and Syverson [75] show that clients' heterogeneous fixed preferences for each of the Big4 auditors vary based on different client

[4]The debate on whether Big N auditors add value or not is ongoing. Lawrence et al. [104] challenge long-standing evidence of positive Big N effects. In this paper, we rely on prior studies that document Big N effects to develop our argument.

characteristics. Additionally, managers make decisions with the aim of maximizing their objective functions (e.g., firm value, financial statement reporting) given a set of inputs; audit services are one of the many mechanisms they may choose (e.g., Fields et al. [63], Dechow et al. [47], Zimmerman [152]). Therefore, managers may choose their auditor based on the unique set of other mechanisms already implemented inside their firms.

Distance factor plays an important role in audit benefits for client's perspective. There exist benefits for being proximate to auditors. The benefits are based on informational advantage that auditors may have by having soft and local information. By interacting with clients more often, observing how the internal audit system works, and understanding the issues in operation more clearly, clients would be able to get better quality audit service. On the other hand, costs for being proximate to auditors also exist. Proximity might increase the audit independence risk. Due to increased personal ties developed between managers in clients and auditors, auditors may be more flexible to managers' discretion on their financial statements, which may lead to restatements.[5]

Clients will consider the net benefits/costs associated with the distance between them and auditors while making their selection on auditors. Because distance is one of many factors that clients may consider selecting their best auditors, clients will trade-off between distance and other auditor factors if those other auditors can give clients higher benefits.

3.2.5 Auditor-Side Trade-Off

From an auditor's perspective, audit costs vary across clients. Similar to the client's perspective, variation in audit costs exists because of (i) heterogeneity in client attributes and (ii) heterogeneity in the value auditors place on those heterogeneous client attributes.

Prior studies provide evidence that auditors have different preferences for specific client

[5]Appendix C provides a graphical and more intuitive explanation of the costs and benefits associated with proximity and other client and auditor attributes.

characteristics. The first evidence of auditors "choosing" clients is commonly referred to as "client portfolio management" in the literature (e.g., Johnstone and Bedard [97]). Johnstone and Bedard [97] show that auditors are more likely to stop providing audit services to clients that have a higher audit risk relative to other incumbent clients. They also document that auditors are more likely to accept new clients with lower audit risk relative to incumbent clients.

Second, auditors' client preferences are also evident in prior studies of audit quality. The evidence of "Big N effects" (e.g., Francis [68], Lawrence et al. [104], DeFond et al. [50]) or "industry expert effects" (e.g., Minutti-Meza [117]) might be driven by better auditors having better-quality clients. This self-selection issue has been addressed as a challenge in audit quality studies (e.g., Francis [68], Hay et al. [88], Lawrence et al. [104], Minutti-Meza [117], DeFond and Zhang [49], Donovon et al. [52]). Such self-selection, i.e., better-quality agents on one side of the market pairing with better-quality agents on the other side of the market, is described as "sorting" behavior in matching market literature in economics (e.g., Gale and Shapley [72], Becker [20], Roth and Sotomayor [135], Sørensen [139], Fox [66]). In this literature, such sorting behavior is commonly referred as the evidence of who prefers whom.

The distance factor plays an important role in audit costs from an auditor's perspective as well. Proximity to clients yields benefits; for instance, because auditors can provide better guidance on internal control systems and offer timelier feedback, they will be able to maintain stronger client-auditor relationships and build a reputation for providing good audit services. On the other hand, auditors increase the risks of threatening audit independence when they are located close to their clients. If auditors apply more lenient audit standards to clients located nearby, auditors will be exposed to costs associated with future reputational loss coming from restatements or PCAOB inspections.

Like clients, auditors will consider the net benefits and costs associated with their distance from client headquarters. Because distance is one of many factors that clients may consider in selecting their clients, auditors will sacrifice lower distance for other client characteristics if the latter can offer higher benefits.

3.3 Identification

3.3.1 One-Sided Decision vs. Two-Sided Decision

Prior studies have used primarily single-agent choice models (e.g., probit, logit, OLS regression model) to understand client-auditor selection and audit fee determination. These models analyze the decision from one side, taking the other side's decision as given. This approach likens client/auditor selections to a simple consumer transactions where only consumer's preference matters, like choosing a soda from a convenience store. In contrast, two-sided matching models assume that agents from both sides take into account the other side's decisions and the equilibrium outcome depends on both.

A match between an auditor and a client is formed by mutual agreement between the two. In other words, the formation of client-auditor matches at equilibrium depends not only on the client's preferences but also on the auditor's preferences (i.e., whether the auditor is willing to provide audit services to that client).

Therefore, it is appropriate to model the audit market as a two-sided market Gale and Shapley [72], Roth and Sotomayor [135]), whereby the market outcome consists of joint decisions by both clients and auditors. A two-sided matching model incorporates these key features, thus allowing us to examine the interplay between auditors and clients from a market-wide perspective. We follow the empirical framework of Fox [65] and Akkus et al. [6]. Using the structure of two-sided matching market models, we jointly model the preferences of auditors and clients regarding their counterparts, including audit fees as an input of their preference functions. We depart from the existing model by changing the fee recipient's function (in our setting, the auditor-side function) to include non-pecuniary terms (in our setting, audit cost terms) and allow for a trade-off between pecuniary terms and non-pecuniary terms. Thus, the novel aspect of our two-sided matching market model is that both sides consider both non-pecuniary terms and pecuniary terms. In other words, audit fees as well as unobserved audit benefits (for clients) and unobserved audit costs (for auditors) are jointly determined.

3.3.2 Match Specific Audit Benefit and Audit Cost Variation

As mentioned in Section 2, it is challenging to properly capture the heterogeneity in the value clients place on heterogenous auditor attributes and vice versa. Prior studies in economics and finance suggest the inclusion of interaction variables of client attributes and auditor attributes as a potential solution (e.g., Roth and Sotomayor [135], Pan [126]). This is similar to the interaction variables used in the client utility model in Gerakos and Syverson [75].

Our model includes not only client attributes and auditor attributes but also interaction variables for both. Adding these variables reflects the idea that different clients (auditors) value the same auditors (clients) differently. Therefore, in contrast to reduced-form estimation, which contains the strong assumption that every client or auditor has homogenous valuation, We assume neither homogenous valuation nor heterogenous valuation. We allow let the data speak to this issue.

3.3.3 Constraints on Client-Auditor Pair Formation: Competition and Bargaining Power

As we alluded in prior sections, prior studies using reduced-form implicitly assume that an agent in the market makes choices independent of other agents. In other words, the discrete choice model makes two strong assumptions: (i) clients choose their preferred auditors independently of other clients; and (ii) auditors choose their preferred clients independently of other auditors (Mindruta et al. [116]).

While discrete choice models may be appropriate in contexts where clients face few constraints in forming relationships with their preferred auditors, their applicability is limited when clients are constrained by competition for desirable auditors. In short, the major shortcoming of the standard choice models is their inability to accommodate the complex structure of correlated errors that emerges due to the constraints in the auditor-choice dimensions imposed by the preferences of all clients participating in the market (Mindruta et al. [116], Train [146], Hay et al. [88]).

We overcome this issue by utilizing the equilibrium concepts embedded in the two-sided matching market models. The equilibrium pairs of clients and auditors are formed only when the pairwise stability condition holds. In other words, the equilibrium matches in the market exist when neither clients nor auditors deviate from their matched pairs. Section 4 provides a more detailed explanation of this concept.

3.4 Empirical Methodology

In this model of auditor-client matching as a two-sided matching game, every auditor-client pair realizes a joint match value, i.e., total surplus. Then, clients and auditors split this total surplus into two by transferring utility via audit fees. Each client (auditor) matches with an auditor (client) who can maximize its payoff given the constraints that it faces in the selection process. In equilibrium, matched clients and auditors receive a higher payoff from observed match partners than they could have received from counterfactual partners.

In the model, we construct many possible counterfactual matches to each observed match within a matching market, generating many inequalities for each observed match. Given these inequalities and a parametric form for the match value function, we choose the parameter vector that maximizes the fraction of inequalities that hold.

We largely follow the rank-order properties introduced by Fox [65, 66] to estimate the two-sided matching markets where stable matches are assumed to be satisfied. The model is based on the two-sided matching models in Akkus et al. [6] and Pan [126], extending on Fox's initial setup of empirical two-sided matching models. The major improvement from the model in Fox [65, 66] to the model in Akkus et al. [6] is that the latter includes the transfer of utility information (i.e., monetary transaction information between two parties).

We develop a related estimator that uses transfer data and allows for auditors' non-pecuniary terms, i.e., audit costs, to be captured in the model. These non-pecuniary terms allow for the estimation of (i) the unobserved audit costs in auditors' payoff functions and (ii) any possible trade-off auditors make among audit costs including audit fees.

3.4.1 Model Setup

For a total number of M_y matches in matching market y, we denote clients by $c = 1, \ldots, M_y$ and auditors by $a = 1, \ldots, M_y$. We assume there is one national audit market for each industry and the markets are independent of one another. The matched pair (c, a) realizes a client-auditor match value of $U(c, a)$, which is a summation of $F(c, a)$ and $G(c, a)$:

$$U(c, a) = F(c, a) + G(c, a) \tag{3.1}$$

where $F(c, a)$ is the client surplus, and $G(c, a)$ is the auditor surplus. The client surplus $F(c, a)$ is composed of audit benefits, denoted by $f(c, a)$, minus audit fees, denoted by $p(c, a)$.

$$F(c, a) = f(c, a) - p(c, a) \tag{3.2}$$

The auditor surplus $G(c, a)$ is composed of audit fees minus audit costs, denoted by $g(c, a)$.

$$G(c, a) = p(c, a) - g(c, a) \tag{3.3}$$

The matched pair (c, a) maximizes its paired value $U(c, a)$ across possible counter factual matches. To attain a general equilibrium of matched pairs in the market, the client c and auditor a in match pair (c, a) is better off than having alternative counter party, e.g., (c, a') for client c or (c', a) for auditor a. Each client c maximizes $F(c, a)$ across auditors. In other words, each client derives higher value from the observed client-auditor match than from any other counter factual match. This inequality concept provides insight into an important identification condition (i.e., pairwise stable condition) in any two-sided matching market (Fox [66], Akkus et al. [6]).

Let's assume the paired matches (c, a) and (c', a') are the observed matches in the market. Because client c is matched with auditor a, we can infer that c derives more value from a than it would have derived from a'. This can be expressed as follows.

$$F(c, a) \geq F(c, a') \tag{3.4}$$

$$f(c, a) - p(c, a) \geq f(c, a') - p(c, a') \tag{3.5}$$

Solving this inequality requires $p(c, a')$, the audit fee that client c would have paid if the client had selected potential auditor a' instead of actual auditor a. Unfortunately, $p(c, a')$ is not observed. Akkus et al. [6] propose overcoming this issue as follows. In equilibrium, each auditor receives the same surplus, $G(c, a')$, across clients; thus, for auditor a', $G(c, a') = G(c', a')$. The logic is the following. Under equilibrium pairs (c, a) and (c', a') Client c', whose equilibrium matching pair is a', would not share additional surplus with auditor a' because a higher auditor surplus would reduce its own payoff. Therefore, $G(c, a') < G(c', a')$

will not hold at equilibrium. Likewise, $G(c,a') > G(c',a')$ would not hold under equilibrium pairs (c,a) and (c',a'). If auditor a' would receive a higher surplus from matching with client c, i.e., $G(c,a') > G(c',a')$, auditor a' would deviate from the current pair c', and therefore, (c',a') would no longer be a stable equilibrium. In sum, $G(c,a') = G(c',a')$ in equilibrium.

$$G(c,a') = G(c',a') \tag{3.6}$$

Using equation (3), we can rephrase equation (6) as the following:

$$p(c,a') - g(c,a') = p(c',a') - g(c',a') \tag{3.7}$$

$$p(c,a') = g(c,a') - g(c',a') + p(c',a') \tag{3.8}$$

Now, replace p(c,a') in equation (5).

$$f(c,a) - p(c,a) \geq f(c,a') + g(c',a') - g(c,a') - p(c',a') \tag{3.9}$$

Pairwise Condition 1:

$$f(c,a) - f(c,a') - g(c',a') + g(c,a') \geq p(c,a) - p(c',a') \tag{3.10}$$

A similar derivation is performed for the inequality $F(c',a') \geq F(c',a)$, yielding the following inequalities:

$$F(c',a') \geq F(c',a) \tag{3.11}$$

$$f(c',a') - p(c',a') \geq f(c',a) - p(c',a) \tag{3.12}$$

Similar to Pairwise Stability Condition 1, $G(c',a) = G(c,a)$ holds at equilibrium. Using equation (3), we can rephrase $G(c', a) = G(c, a)$ as the following:

$$p(c, a) - g(c, a) = p(c^{'}, a) - g(c', a) \tag{3.13}$$

$$p(c', a) = g(c', a) - g(c, a) + p(c, a) \tag{3.14}$$

Now, replace $p(c', a)$ in equation (12).

$$f(c', a') - p(c^{'}, a^{'}) \geq f(c^{'}, a) - g(c^{'}, a) + g(c, a) - p(c, a) \tag{3.15}$$

Pairwise Condition 2:

$$f(c', a') - f(c^{'}, a) - g(c, a) + g(c^{'}, a) \geq p(c', a') - p(c, a) \tag{3.16}$$

3.4.2 Estimation of Matching Model

To use the maximum-score estimator, we specify a functional form for client's audit benefits and auditor's audit costs as follows:

$$f(c, a) = \alpha X_a + \beta X_c X_a + \gamma X_c a + \varepsilon_{(c,a)} \tag{3.17}$$

$$g(c, a) = \bar{\alpha} X_c + \bar{\beta} X_a X_c + \bar{\gamma} X_c a + \varepsilon_{(c,a)} \tag{3.18}$$

where X_a represents auditor attributes and X_c represents client attributes. Therefore, the audit benefit function for clients, $f(c, a)$, depends on auditors' independent characteristics and their interactions with client characteristics. The audit cost function for auditors, $g(c, a)$, depends on the independent effects of client characteristics and their interaction effects with auditor characteristics. We examine two auditor characteristics: industry expertise and whether the auditor is a Big N accounting firm. We examine four client characteristics: size, financial condition, absolute discretionary accruals (ADA), and audit governance. X_{ca} represents the client-auditor pair characteristics, which are jointly determined at the pair level. Two variables are considered: distance and tenure. Distance, the main variable of interest, is the distance between the client headquarters location and auditor office location. We also add the interaction variables of distance and client characteristics. The Tenure of the client-auditor relationship in years (as of the beginning of the fiscal year) is the last variable in the functional form. $\varepsilon_{(c,a)}$ is the match-specific error term that we assume to be independent across matches in our dataset. We use a maximum score estimator similar to Fox [65, 66] and Akkus et al. [6].

We estimate the set of parameters (ω) that maximizes the objective function:[6]

$$
\begin{aligned}
Q(\omega) = \sum\sum\sum 1[&f(c,a|\omega) - f(c,a'|\omega) - g(c',a'|\omega) + g(c,a'|\omega) \\
\geq & p(c,a|\omega) - p(c',a'|\omega) \bigcap f(c',a'|\omega) - f(c',a|\omega) - g(c,a|\omega) + g(c',a|\omega) \\
\geq & p(c',a'|\omega) - p(c,a|\omega)]
\end{aligned}
\tag{3.19}
$$

3.4.3 Obtaining the Functional Form

This section presents the functional form of the objective function (19). Equation (19) can be rephrased using the functional form specified in equations (17) and (18). The functional form of Pairwise Stability Condition 1 is

$$
\begin{aligned}
X_a + \beta X_c X_a + \gamma X_{ca} - \alpha X_{a'} - \beta X_c X_{a'} - \gamma X_{ca'}) - (\bar{\alpha} X_{c'} + \bar{\beta} X_{c'} X_{a'} + \bar{\gamma} X_{c'a'} - \\
\bar{\alpha} X_c - \bar{\beta} X_c X_{a'} - \bar{\gamma} X_{ca'}) \geq p(c,a) - p(c',a')
\end{aligned}
\tag{3.20}
$$

[6] The first inequality in the objective function is Pairwise Stability Condition 1 and the second inequality is Pairwise Stability Condition 2.

$$\alpha(X_a - X_{a'}) + \beta(X_c X_a - X_c X_{a'}) + \gamma(X_c a - X_{ca'}) + \bar{\alpha}(X_c - X_{c'}) + \bar{\beta}(X_c X_{a'} - X_{c'} X_{a'}) + \bar{\gamma}(X_{ca'} - X_{c'a'}) \geq p(c,a) - p(c',a') \tag{3.21}$$

The functional form of Pairwise Stability Condition 2 is the following.

$$(\alpha X_{a'} + \beta X_{c'} X_{a'} + \gamma X_{c'a'} - \alpha X_a - \beta X_{c'} X_a - \gamma X_{c'a}) - (\bar{\alpha} X_c + \bar{\beta} X_c X_a + \bar{\gamma} X_{ca} - \bar{\alpha} X_{c'} - \bar{\beta} X_{c'} X_a - \bar{\gamma} X_{c'a} \geq p(c',a') - p(c,a) \tag{3.22}$$

$$\alpha(X_{a'} - X_a) + \beta(X_{c'} X_{a'} - X_{c'} X_a) + \gamma(X_{c'a'} - X_{c'a}) + \bar{\alpha}(X_{c'} - X_c) + \bar{\beta}(X_{c'} X_a - X_c X_a) + \bar{\gamma}(X_{c'a} - X_{ca}) \geq p(c',a') - p(c,a) \tag{3.23}$$

3.4.4 Subsampling of Confidence Interval

To generate point estimates, we run the differential evolution optimization routine from 10 different starting points and select the set of parameter estimates that generate the highest value for the above objective function. For statistical significance, we subsample 1/3 of total sample and take 100 randomly selected subsamples (S =100) to construct confidence intervals. For each of the 100 subsamples, we estimate the set of parameters that maximizes the above objective function and recover the sampling distribution for the parameters. The sampling distribution for the set of parameters can be computed as follows:

$$\omega_s = (n_s/N)^{1/3}(\omega_s - \omega_{full}) + \omega_{full} \tag{3.24}$$

where ω_s denotes the parameter estimates from the sth subsample, ω_{full} denotes the parameter estimates from the original full samples, N denotes the observations in the full sample, and n_s denotes the observations in a subsample. The procedure accounts for the $N^{1/3}$ convergence of the maximum score estimator. We calculate the 95% confidence intervals for the set of parameters by taking the 2.5th percentile and the 97.5th percentile of these sampling distributions.

3.5 Data

We collect data from the Audit Analytics, Compustat, and BoardEx databases. The data span all client-auditor matches in the United States for fiscal year 2015 that have the necessary data for variable calculation available. At the beginning date of year 2015, we calculate client characteristics, auditor characteristics, client-auditor pair characteristics. The main variable of interest is the Distance between the client headquarters and the auditor office. We define these locations at the state-city level and use longitude and latitude to calculate the distance between them. We consider four client characteristics. Size is defined as the natural log of a client's total assets. Financial Condition is the natural log of the Altman Z score. Absolute Discretionary Accruals (ADA) is a proxy for the level of managers' discretion in financial statements, measured as the natural log of the absolute number of discretionary accruals using the modified Jones model and adjusting performance following Kothari et al. [102]. Audit Governance is defined as the number of audit committee members divided by the total number of board members.

We consider two auditor characteristics: auditor industry expertise and Big N. Auditor characteristics are defined at the auditor office level. We identify the auditor office for each year from Audit Analytics – Audit Opinions. Auditor Industry Expertise is defined as the total assets of an auditor's clients in a given industry divided by the total assets of all firms in that industry. Industry is defined by two-digit SIC. Big N is an indicator variable equal to 1 if the audit office is one of the Big N audit offices.

Table 3.1 reports the summary statistics. Though we only use year 2015 data, We represent year by year sample from year 2000 to year 2015 in Panel A. Panel A. provides yearly information on the number of total client-auditor matches, client-auditor matches where auditors are Big N accounting firms, and client-auditor matches where auditors are non-Big N accounting firms. Similar to the findings in Aobdia et al. [10], client-auditor matches for Big4 auditors decrease while matches for non-Big4 auditors increase over time. Panel B. shows the descriptive statistics of final sample (only year 2015) of client characteristics, auditor characteristics, and audit fee. The mean audit fee in this sample is $2,282,081

3.6 Results

In this section, We first present results estimating the effect of distance on client and auditor surplus. Second, We document the loss of market-wide total surplus due to stickiness of auditor office locations. Third, We examine cross-regional variation in audit market performance. Finally, We document the effect of audit office re-location and openings on market-wide surplus in local audit markets.

3.6.1 The Effect of Distance on Client/Auditor Surplus using Structural Form Estimation

We conduct a structural estimation using the estimation model (equation 19). Panel A of Table 3.2 presents the estimation results for audit benefits on the client side, or f(c,a) in equation (2) and (17). Panel B presents estimation results for audit costs on the auditor side, or g(c,a) in equations (3) and (18). In column (1) of Panel A and Panel B, We estimate parameters with standalone auditor characteristics variables as well as interaction variables of client attributes and with auditor characteristics. In column (2) of Panel A and Panel B, We include interaction variables of distance with client characteristics.

First, % of Satisfied in column (1) and column (2) tells us how well the model is specified. Both column (1) and column (2) have values of about 99.7% for the % of Satisfied, which suggests that the estimated parameters meet the pair-wise stability condition by 99.7% of the time. In other words, this model almost fully explains the matching pattern.

In column (1) of Panel A, the Distance variable is significantly negative at the 5% level. The negative coefficient shows that, on average, a higher distance between client headquarters and auditor offices reduces client surplus. The coefficient value of -1,948.1 implies that a 50% increase in distance relative to paired client-auditor distance will reduce the client surplus by $11,688, which is approximately 1.9% of the average client surplus.

In column (2) of Panel A, we include interaction terms, interacting distance with other client characteristics, which allows us to make two additional inferences. First, We can document the variation in the impact of distance on client surplus conditional on client characteristics. Second, we can isolate the trade-off between proximity and auditor characteristics conditional on each client characteristics.

The interaction of Size and Distance is statistically negative at the 5% level. The negative coefficient suggests that as client size increases, the value clients place on proximity to auditors increases on a per-unit basis. In other words, a higher distance from auditors lowers larger clients' surplus more substantially.

Size also impacts how clients weigh the costs associated with higher distance against auditor industry expertise. The interaction of Size and Auditor Industry Expertise is significantly positive, suggesting that as size increases, larger clients value industry expertise disproportionately more than smaller clients (on a per-unit basis). Thus, the decreases in client surplus associated with a higher distance from auditors can be mitigated by additional auditor industry expertise. In other words, even if Auditor A is located farther from a client than Auditor B, the client could retain Auditor A if its industry expertise relative to Auditor B is sufficiently high. Table 3.3 reports trade-off conditional on size. For clients in between 50th percentile and 75th percentile of size distribution, clients should get auditors with at least 53% higher industry expertise relative to their paired-auditor's industry expertise to mitigate the loss of surplus from 10% increase of distance relative to the distance between client location and paired-auditor location. The test results in Table 3.3 suggest that the trade-off between distance and auditor industry expertise shows decreasing trend moving from small size clients to large size clients.

The interaction term of Audit Governance and Distance is significantly positive. This suggests that, conditional on a client's audit-related governance structure, higher distance from auditors generates a higher client surplus, on average. Clients with better-quality audit governance systems benefit more from increases in distance, on a per-unit basis, than those with lower-quality audit governance systems. Also, the interaction term of Audit Governance and Auditor Industry Expertise is significantly negative. Clients with better-quality of audit governance systems value disproportionately less for an additional unit increase of auditor industry expertise than those with lower-quality audit governance systems. Therefore, conditional on audit-related governance quality, lower auditor expertise can mitigate the loss of surplus from being more proximate to auditors. This might be somewhat counterintuitive. However, this trade-off between distance and auditor expertise conditional on audit-related governance quality might be related to the fact that the internal audit function and the external audit function are, to a degree, substitutes for each other. Table 3.3 exhibits that for clients in between 25th percentile and 50th percentile of Audit Governance variable distribution, clients should get auditors with at least 89% higher industry expertise relative to their paired-auditor's industry expertise to mitigate the gain of surplus from 10% increase of distance relative to the distance between client location and paired-auditor location.

Panel A of Table 3.2 contains additional important results. First, the interaction variable of ADA (absolute discretionary accruals) with Distance is statistically insignificant and negative. This shows that, as the level of discretion in financial statements increases, clients with higher discretion level in financial statements value disproportionately less for a unit increase of distance than clients with lower discretion level in financial statements do. Prior studies present some evidence that clients' receiving audit services from distant auditors may be doing so for opportunistic purpose (Choi et al. [36], Jensen et al. [95]). Although the coefficient in this paper is not statistically significant and its magnitude is relatively small, its negative sign contradicts the opportunistic choice hypothesis.

Second, the interaction variables of client characteristics and auditor characteristics exhibit the complementarity/substitutability relation between the two. We highlight two variables: Audit Governance interacted with Auditor Industry Expertise and Audit Governance interacted with Big N. The interaction variable of Audit Governance with Auditor Industry Expertise is negative while the interaction variable of Audit Governance with Big N is positive. The results suggest that audit governance is substitutable for auditor industry expertise: on a per-unit basis, clients with better audit-related governance systems value auditor industry expertise less than clients with poor audit-related governance systems do. On the other hand, clients with better audit-related governance systems value Big N auditors more than clients with poor audit-related governance systems do. These results suggest that clients with better audit governance systems demand less auditor expertise but value other unique audit functions (orthogonal to auditor expertise) of Big N auditors (e.g., reputation).

Panel B of Table 3.2 documents auditor-side results. Distance is positively related to audit costs at 5% level.[7] The positive coefficient suggests that on average, increases in distance between client headquarters and auditor office reduce auditor surplus. A few important differences exist between the impact of distance on client surplus and auditor surplus. First, distance affects auditor surplus more than client surplus. Based on the coefficient value for

[7]Note that the parameters on the auditor side estimate audit costs, g(c,a) in equation (3).

the former (2880.5), a 50% increase in distance relative to paired client-auditor distance reduces auditor surplus by $17,280 on average, which is approximately 2.8% relative to average auditor surplus. Second, auditors have fixed preferences for proximity. Even after including interaction terms, the standalone impact of distance in the auditor-side estimation does not vary conditional on client characteristics as much it varies on the client side.

3.6.2 Do Clients Get Audits from Worse Auditors because their Preferred Auditors are Located Farther Away?

The prior section suggests that, on average, increases in distance generates lower surpluses for both clients and auditors. Although these distance-related surplus losses would be completely mitigated if auditor offices were locate next to every client headquarters, the costs of implementing such a strategy would almost certainly outweigh the benefits. This idea motivates the tests conducted in this subsection. In particular, we examine whether clients forgo potential alternative auditors with better match value but located farther from their headquarters than their actual paired-auditors because the costs of greater distance outweigh any benefits the alternative auditor offers. If clients forgo better auditors because the location of auditors is too far away from client headquarters, this represents that clients would rather choose alternative auditors if the alternative auditors were located in the same distance with their paired-auditors. Because additional benefits coming from the alternative auditor are greater than the benefits from the matched-auditor, those additional benefits are a loss of value caused by the immobility of auditor office locations, i.e., friction. In this section, we examine to what extent such friction exists in the overall audit market.

One simple way of documenting the extent of the friction caused by immobility of audit office locations is comparing the surpluses of the following: (i) the predicted new equilibrium pairs assuming office location does not matter and (ii) the actual equilibrium pairs assuming office location does not matter. A simple intuitive illustration at a micro-level could be outlined as follows. Suppose client C1's current auditor, BDO, is located 40 miles away. There is another audit office, PWC, located 120 miles away from C1. The PWC office has higher audit expertise than the audit expertise that C1's current auditor, BDO, has. However, because the costs associated with 80 additional miles for PWC exceed benefits of higher audit expertise for PWC, C1 retains BDO for its audit services at equilibrium. If the PWC office had been as close as BDO, in contrast, C1 would have chosen PWC and generate additional benefits from higher industry expertise. Of course, not all clients would benefit in such a scenario, because there is a limited set of auditors to choose from, and the ideal auditor for a client may simply not exist (or already be retained by another client). Therefore, some clients may be worse-off. The extent to which the loss of surplus caused by immobility of audit office locations impacts the audit market overall is an empirical question.

Table 3.4 reports the results of the above counter-factual analysis. The results show that the average total surplus of actual pairs when the distance between the client and auditor locations does not matter is $1,351,520. Under the new equilibrium pairs predicted following the matching process described in Baccara et al. [13], the average total surplus increases by $21,920 (approximately 1.6%). 166 clients are left better-off, while 55 are left worse-off and 2,002 experience no change. Note that these results take the tenure effect into account. Without the effect of tenure on client-auditor matching, the new predicted equilibrium pairs generate a 17% higher surplus and the majority of clients are better-off. Overall, the results suggest that, on average, due to the immobility of audit office locations, a substantial loss of welfare occurs in the audit market and a significant number of clients experience loss of surplus.

3.6.3 Cross-Region Variation of Local Audit Markets

We now examine the variation across local audit markets in (i) market participants' economic welfare (i.e., total surplus) and (ii) how this surplus is split between clients and auditors. The base level of local audit market variation in this study is the metropolitan statistical area (MSA). MSA-level analysis is consistent with prior studies (e.g., Newton et al. [119], Dunn et al. [54], Numan and Willekens [122]). We calculate the ratio of the number of auditors to the number of clients for each MSA (auditor/client ratio) and compare this ratio across MSAs. We take the 10 regions with the highest (lowest) ratios and define them as overserved (underserved) regions.

Table Table 3.5 presents descriptive statistics for under- and overserved MSA regions; a list of all MSAs can be found in Appendix A. Panel A of Table 5 depicts the Auditor/Client Ratio for underserved areas; it ranges from 0 to 0.174, and remains similar when considering only Big N auditors and their clients. Panel B shows the Auditor/Client Ratio for overserved areas, which ranges from 0.386 to 0.917. Auditor/Client Ratio is at least twice as large in the overserved regions as in underserved regions. Figure 1 presents a graphical representation of Auditor/Client Ratio across states, presented at the state level for simplicity. Texas and California are examples of underserved regions at the state level, while Missouri and Florida are examples of overserved regions.

In Table 3.6, we examine total surplus and auditor surplus ratio across different regions. Auditor Surplus Ratio is defined as auditor surplus divided by total surplus. For each individual pairs, both clients and auditors can be located in either an overserved MSA, an underserved MSA, or a MSA that is neither over- nor underserved (We refer to these regions as middle MSAs). The first three rows of Panel A of Table 3.6 represent client-auditor pairs for which clients' headquarters are located in an overserved MSA. The next three rows represent client-auditor pairs for which clients' headquarters are located in an underserved

MSA. The last three rows represent client-auditor pairs where clients' headquarters are located in an MSA that is neither under- nor overserved.

Client-auditor pairs in which both clients and auditors are located in overserved areas show an average total surplus of \$1,245,660. Client-auditor pairs in which both clients and auditors are located in overserved areas show an average total surplus of \$1,203,130 - marginally lower than overserved areas. Interestingly, middle MSAs have the highest average total surplus: \$1,402,080. The average total surplus is higher for client-auditor pairs in which both parties are located in the same MSA relative to paired clients and auditors located in different MSAs. This is partly driven by shorter distance between client and auditor locations. Turning to auditor surplus ratio, client-auditor pairs in which both parties are located in underserved MSAs have the highest auditor surplus ratios. These results suggest that auditors have bargaining power over clients in areas where fewer auditors compete, allowing them to extract rents by charging relatively higher audit fees compared to other regions.

Panel B presents the Spearman correlation between Auditor/Client Ratio and other variables at the individual client-auditor pair level. Auditor/Client Ratio has a positive but insignificant relation with Total Surplus. This relation might be consistent with the MSA-level evidence that total surplus is highest in the middle MSAs. In contrast, Auditor Surplus Ratio and Auditor/Client Ratio are negatively correlated, indicating that a greater number of auditors in a local market results in a loss of bargaining power and a decrease in audit fees relative to audit costs. Viewed together with the negative but insignificant correlation between Auditor/Client Ratio and Audit Fee, the negative coefficient on Auditor Surplus Ratio suggests that audit fees alone, which have been the main focus of prior studies, may not be sufficient to make accurate inferences without taking audit costs into account.

Panel C compares first-best pairs to actual pairs. The first-best pair is defined as the client-auditor pair that provides clients with the highest surplus among all possible auditors.

The actual pairs are the client-auditor pairs observed in the audit market at equilibrium. For some clients, these pairs might overlap; for others, they differ. Comparing first-best pairs to actual pairs across local audit markets will provide insight into how much loss of surplus exists across these markets due to clients' inability to engage with their ideal auditors, i.e., audit market friction. Clients are least likely to match with their preferred auditors in underserved MSAs and most likely to do so in overserved MSAs; in other words, as clients have a larger auditor pool to choose from, they are more likely to be matched with their ideal auditor. Consequently, the total surplus lost due to friction is lowest in overserved MSAs.

3.6.4 The Effect of Relocating Auditors from Overserved MSAs to Underserved MSAs

In the prior section, we show that both overserved and underserved MSAs exhibit lower total surplus and that auditors in underserved MSAs may exercise their relatively higher bargaining power by extracting rents from clients. In this section, we perform a counter-factual analysis of the consequences of relocating auditor offices from overserved areas to underserved areas. Specifically, we examine how the total surplus in underserved and overserved regions would change if one randomly-selected auditor in each of the 10 overserved regions is relocated to one of the 10 underserved regions (one auditor per region). We perform 20 iterations of this random selection process and report the average results of those 20 iterations. We predict a new equilibrium matching pairs and calculate pair-specific total surplus following the matching process described in Baccara et al. [13].

Table 3.7 shows that relocating auditor offices from overserved to underserved MSAs can improve the economic welfare of both regions. Accounting for the effect of tenure in the client-auditor matching process, relocating audit offices increases average total surplus by 0.34% in underserved MSAs and 0.28% in overserved MSAs. Ignoring the tenure effect, the average total surplus increases by 3.41% and 2.73% in underserved and overserved MSAs, respectively.

3.6.5 The Effect of New Auditors Entering a Local Audit Market

In this section, we perform two additional analyses by focusing on specific audit markets at the state level. Conducting a counter-factual analysis for a specific local audit market allows us to track individual equilibrium pair changes under different scenarios and gain insights into the consequences of structural market changes in the market. Additionally, if regulators and policy-makers are particularly interested in a particular local audit market, these analyses offer a blueprint for studying that market.

We first examine the effect of auditor entry into a local audit market, focusing on the chemical and allied manufacturing industry (SIC = 28) in California. We select this market because California generates one of the lowest total surpluses among all states, and chemical and allied manufacturing generates one of the lowest total surpluses among all industries. The majority of clients in the chemical and allied manufacturing industry are located in California.

As Figure 3.4 shows, clients and auditors are clustered in two California regions: the area around San Francisco (Area 1) and the area around Los Angeles (Area 2). Table 3.8 Panel A-1 presents descriptive statistics for this local audit market. The number of chemical and allied manufacturing industry clients located in California is 112, about a quarter of total clients in the state. The average total surplus for these client-auditor pairs is $637,810, which is about 36% less than the average total surplus for all client-auditor pairs in California. The average distance between clients and auditors is 114 miles, which is about 40% greater than the average distance between all clients in California and their respective auditors (81miles). Among the 112 chemical and allied manufacturing industry clients, 5 are paired with auditors outside California and 3 are paired with auditors in a different area of the state (e.g. clients located in Area 1 receive audit services from auditors located in Area 2).

We examine a situation where one audit office enters Area 1 and another enters Area 2. Table 3.8 Panel A-2 reports the test results. The location of each new entering auditor is the midpoint of incumbent auditor locations in each area. We simulate different scenarios by varying the auditors' characteristics, i.e., auditor industry expertise, Big N classification, and the number of clients auditors can accept. In Case #1, the entering auditors are non-Big N auditors with average industry expertise and the same capacity as the average incumbent auditors in the area. In this scenario, the overall total surplus in these areas increases by 1.2% and one client who previously matched with an auditor outside California now switches to a local auditor. If the entering auditors are Big N auditors, total surplus increases by an additional 0.2%. If the entering auditor has more capacity to handle clients, total surplus increases by an additional 0.8% (See Case #2 and #3).

In sum, auditor entrance into the California audit market increases market-wide total surplus. Moving from Case #1 to Case #4, the results in Table 3.8 suggest that Big N auditors with higher industry expertise and higher resource capacity will incrementally affect total surplus. Also, clients who engage auditors outside California will be incentivized to work with local auditors. However, the three clients who receive audit services from a different area of the state continue to do so under the new market equilibrium.

In Panel B, we examine the effect of auditor office relocation in a slightly different way, considering individual auditors' office management strategies. Specifically, we analyze the consequences of the following hypothetical situation: KPMG closes its St. Louis office and moves it to Las Vegas. The motivation of this analysis is the following. We desire to provide audit firms with an approach for conducting a cost and benefit analysis to evaluate opening, closing, or relocating audit offices. It differs from the counterfactual analysis in Table 3.7 because it is based on each auditor's office management objectives, while the analysis in Table 3.7 is based on social planners' objectives – maximizing the total audit market welfare. We focus on the Las Vegas area since it is one of the fastest-growing MSAs in America; St. Louis, in contrast, is selected as representative of an MSA that does not attract many client headquarters. Therefore it would be a reasonable strategy for KPMG to open an office in the Las Vegas area.

KPMG's St. Louis office provides audit services to one client in the business services industry (SIC = 73). In Nevada, there are two clients in the business services industry, both located in Las Vegas. Those two clients receive audit services from non-Big N auditors located outside of Nevada. If the KPMG office moves to Las Vegas, the St. Louis client will continue to receive audit services from KPMG rather than switching to a different auditor. However, because the distance between the client headquarters and audit office location is greater, total surplus will decrease. Under the new predicted equilibrium matches, the two clients in Las Vegas also continue to get audit services from their current auditors. The hypothetical total surplus for pairing with the KPMG office in Las Vegas is \$540 and \$-3,200 for the client with GVKEY of 178494 and the client with GVKEY of 066261, respectively. Therefore, there is no reason for the Las Vegas clients to switch to the new KPMG office.

Although the KPMG office in Las Vegas will not be able to provide audit services to those two clients under the predicted equilibrium, the following strategy would enable it to do so. Assuming that the two incumbent auditors are not willing to bear the negative surplus of providing audit services to clients, KPMG's Las Vegas office will be able to provide audit services to those clients if it is willing to bear \$506,930 in additional costs for the client with GVKEY of 178494 and \$185,110 additional costs for the client with GVKEY of 066261. Then, both clients would be better off using KPMG's Las Vegas office instead of their current auditors. The additional costs that the KPMG Las Vegas office bears in Year 1 can be recovered in Year 2 for GVKEY of 066261 and in Year 3 for GVKEY of 178494.

3.6.6 What Does Total Surplus Represent? Shareholder Value vs. Agency Costs

Conceptually, the estimated surplus, particularly client surplus and total surplus, may in part represent agency costs. That is, surplus measures may reflect managers' willingness to reap opportunistic benefits that may reduce shareholder value. We argue both conceptually and empirically that surplus measures capture shareholder value, i.e., the higher the surplus, the higher the shareholder value.

The client surplus measure estimated in this paper is conceptually same as the client surplus measure estimated in Gerakos and Syverson [75] and Guo et al. [85]. Gerakos and Syverson [75] argue that the empirical evidence documented in their paper – the positive association between tenure and surplus – is in line with evidence from prior studies documenting a positive association between tenure and shareholder value. Prior studies provide evidence that audit quality increases over audit firm tenure (e.g., Johnson et al. [96], Myers et al. [118], Ghosh and Moon [76], Chen et al. [33]). Because we find a similar relation between tenure and client surplus in our estimation, the estimated client surplus in our model represents shareholder value. Additionally, even if some part of the client surplus reflects managers' opportunistic benefits, total surplus is more robust in representing shareholder value. The definition of total surplus is the sum of client surplus and auditor surplus, or the difference between unobserved audit benefits and audit costs. Therefore, even if some portion of audit benefits reflects agency costs, those opportunistic benefits are canceled out by the portion captured in audit costs. In other words, any potential opportunistic benefits that clients may enjoy by having auditors who may allow opportunistic behaviors will exert costs on auditors (for instance, in the form of future reputational loss).

Nonetheless, we empirically test whether total surplus reflects shareholder value. We regress audit quality measures on pair-specific total surplus. Table 3.9 presents the test results. The first column presents results using absolute discretionary accruals, the second column presents results using restatements, and the third column presents results using auditor change in the next period. Total surplus is negatively associated with absolute discretionary accruals, restatements, and auditor changes. These empirical results support our argument that total surplus represents shareholder value rather than agency costs.

3.6.7 Does proximity add value to clients – Does proximity improve audit quality?

In this section, we examine whether clients having proximate auditors adds have better quality financial statements by having better quality audits. There has been long existing literature in audit on whether higher quality auditors provide better quality of audit services to their client firms. The ultimate goal of these papers are trying to answer the following questions on whether client firms are value added by better quality auditors. Becker et al. [19] document that compare to clients of non-Big six auditors, clients of Big six auditors have lower signed and absolute discretionary accruals, providing evidence of Big six auditors are associated with less client firms' earnings management. Willenborg [148] finds national-wide Big N auditors are negatively associated with IPO underpricing. Mansi et al. [110] document the evidence of audit firm size and tenure (duration of client relationship) is negatively associated with cost of debt. Additionally, using the auditors' within-industry market share as the auditor industry specialization, prior studies find a positive association between auditor industry specialization and clients' earnings response coefficients (Balsam et al. [18]), and a negative association between auditor industry specialization and the clients' absolute value of discretionary accruals Reichelt and Wang [132]).

Though many prior studies document a positive relation between cross-section variation of auditor quality and some outcome measures of client firms, these studies contain the issues of endogeneity, more precisely self-selection issues (e.g., Francis [68], Lennox et al. [105], DeFond and Zhang [49]). The association between the proxies of auditor quality and the clients' outcome variables might be reflecting the fact that higher quality auditors' client firms are better than lower quality auditors' client firms. The association might be correlated with both observed and unobserved characteristics of client firm characteristics. More recent papers challenge prior studies' findings on higher quality auditors being associated with better outcome of client firms. Lawrence et al. [104] document the association between Big N auditors and discretionary accruals, cost of equity, and analyst forecast accuracy disappear once they match Big 4 and non-Big 4 client firm characteristics.[8] Minutti-Meza [117] also document that there is no evidence of differences of outcome variables (absolute discretionary accruals, meet-or-beat analyst forecast, auditors' propensity to issue going concern opinions) between industry specialist auditors and non-industry specialist auditors after matching client firms' characteristics in the number of dimensions.Lennox et al. [105] document the "fragility of inferences" on prior studies that document the relation between Big N auditors and audit outcomes (e.g., discretionary accruals, cost of capital) using Heckman selection model.

We use the matching equation model that we use in this paper to control the sorting effects and identify the effect of distance on the audit quality. This method is similar to the models in Akkus et al. [5]. Specifically, we use the following two-stage equation.

The first stage is estimating the equation (19). In this section, we only use six variables: distance, tenure, Big N, auditor industry expertise, size, and financial condition. Table 3.10. Panel A presents result of the first-stage estimation using those six variables. Similar to Table 3.2 results, distance is significantly negative for clients.

[8]DeFond and Zhang [48] rebut Lawrence et al. [104] and document the sensitivity of results in Lawrence et al. [104] by using different variable definitions, different proxies of audit outcomes, and different matching methods.

Once we estimate the first stage, then we estimate the following second stage equation.

$$FSQ_{ca} = \gamma(P_{ca} - \beta X_{ca}) + \delta_{ca} \tag{3.25}$$

, where FSQ_{ca} is the proxy of financial statement quality in year 2016, P_{ca} is the proxy of U_{ca}, i.e., match value of client-auditor, βX_{ca} is the product of first-stage estimated coefficients (β) and the client and auditor characteristics (X_{ca}), and δ_{ca} is independent of P_{ca} and X_{ca}.[9]

Table 3.10 Panel B presents results of equation (25). Distance_client is significantly negative at 10% level. This shows that the effect of increase of distance on client utility negatively affects financial statement quality measured by absolute discretionary accruals in the following year after client-auditor match.

3.7 Conclusion

This paper uses surplus estimation to examine the effect of auditor location on the audit market. By utilizing two-sided matching market models developed in the economics literature, we identify unobserved audit benefits that clients receive from their auditors, as well as unobserved audit costs that auditors incur by providing audit services to their clients. This allows us to estimate the effect of distance between client headquarters and auditor offices on client and auditor surplus.

Because auditor location matters for on-site examination and providing feedback on internal control systems, a greater distance between the client headquarters and the auditor office reduces both client and auditor surplus, on average. The sensitivity of client surplus to distance varies based on client characteristics. Bigger clients place a higher value on proximity to auditors than smaller clients, while clients with better audit governance systems benefit more from engaging a more distant auditor compared to clients with poor audit

[9] Akkus et al. [5]documents detail explanation on model setups.

governance.

Using the estimated parameters, we also examine the audit market structure, quantifying the market friction driven by the stickiness of auditor office locations. First, we document the market-wide loss of surplus due to immobility of audit offices. About 8% of clients would have been better off if an alternative auditor office (located farther out) had been as close as their actual paired auditor, leading to a 1.6% loss of market-wide total surplus. These results suggest that auditor office stickiness generates friction, leading clients to match with less preferred auditors. Additionally, this paper documents that clients in underserved audit markets are less likely to find auditors that are a good fit for them relative to clients in overserved audit markets. Auditors in underserved markets charge higher audit fees relative to their audit costs compared to auditors in overserved markets. The simulation results suggest that audit office relocations and openings can mitigate these issues.

The findings in this paper can inform the work of policymakers, regulators, and auditors. The new approach and the estimation model that we propose are useful for understanding various dimensions of audit benefits and costs. Also, by taking advantage of the structural estimation approach to estimate both client and auditor surplus, our model can be useful for predicting the consequences of changes in the audit market environment, including regulatory changes.

Table 3.1: Descriptive Statistics

Panel A reports the number of client-auditor matches by year. Panel B reports summary statistics for the final sample of client characteristics, auditor characteristics, and mutual characteristics used in subsequent analyses.

Panel A. Number of Matches by Year

Year	Client-Auditor Matches	Distance	BigN Matches	Distance	Non BigN Matches	Distance
2000	535	0.1197	523	0.1191	12	0.1484
2001	1,035	0.1202	1,013	0.1188	22	0.1855
2002	1,125	0.1213	1,096	0.1174	29	0.2691
2003	2,367	0.1359	2,051	0.1219	316	0.2266
2004	2,646	0.1324	2,152	0.1166	494	0.2014
2005	2,731	0.1292	2,043	0.1134	685	0.1764
2006	2,669	0.1297	1,910	0.1100	759	0.1792
2007	2,705	0.1289	1,796	0.1009	909	0.1842
2008	2,571	0.1300	1,713	0.0959	858	0.1981
2009	2,421	0.1235	1,632	0.0941	789	0.1843
2010	2,307	0.1205	1,589	0.0901	718	0.1876
2011	2,273	0.1186	1,555	0.0827	718	0.1964
2012	2,242	0.1132	1,558	0.0798	684	0.1892
2013	2,282	0.1114	1,566	0.0668	716	0.2090
2014	2,347	0.1133	1,576	0.0690	771	0.2040
2015	2,223	0.0958	1,491	0.0575	732	0.1739

Panel B.

Variable	Obs.	Mean	25th	50th	75th
Distance	2,223	0.095	0	0.013	0.033
Size	2,223	6.224	4.700	6.263	7.843
Financial Condition	2,223	0.968	0.699	1.323	1.780
ADA	2,223	0.152	0.034	0.077	0.183
Audit Governance	2,223	0.443	0.357	0.441	0.511
Auditor Industry Expertise	2,223	0.019	0.0002	0.003	0.015
Big N	2,223	0.671	0	1	1
Tenure	2,223	6.339	2	5	12
Audit Fee	2,223	2,282,081	425,750	1,088,580	2,399,000

Table 3.2: Maximum Score Structural Estimation

This table presents the results of the match value function (equation 19) using maximum score estimation. Panel A shows the estimation results of the client value function (equation 17). Panel B shows the estimation results of the auditor value function (equation 18).

	Panel A: Client		**Panel B: Auditor**	
	(1)	**(2)**	**(1)**	**(2)**
Distance	-1948.1^	924.8	2880.5^	2247.9^
Size			32.6	20
Financial Condition			-6.8	-34.4
ADA			16.4	33.7
Audit Governance			-74.7^	-1326^
Big N	-3693.1	-6100.8		
Auditor Industry Expertise	-8396.3	-5352.7		
Size*Distance		-928.5^		164.4^
Financial Condition*Distance		330.8		53
ADA*Distance		-2.5		-354.1^
Audit Governance*Distance		1996.0^		-35.2
Size*Auditor Industry Expertise	2578.7^	1912.0^	-7956.7^	-2098.8^
Size*Big N	682.3^	926.6^	-232.3^	-940.3^
Financial Condition*Auditor Industry Expertise	-5520.8	-5576.9	8152.9^	9335.5^
ADA*Auditor Industry Expertise	-2008.9	-6997.7	7939.1^	5339.8
Audit Governance*Auditor Industry Expertise	-9626.6^	-728.8^	-2539.5	5167.5
Financial Condition*Big N	196.9^	911.2^	-109.1	336
ADA*Big N	179.3^	407.3^	-167.1^	-194.2
Audit Governance*Big N	1197.3^	3073.7^	1240.0	6012.1
Tenure	9985.4^	9601.4^	-9761.7^	-9975^
No. of Pairs	208,397	208,397	208,397	208,397
% of Satisfied	0.99729	0.99733	0.99729	0.99733

Table 3.3: Trade-off between Distance and Auditor Industry Expertise

This table presents the trade-offs that clients make between distance and auditor industry expertise. We exploit the following situation: how much auditor industry expertise must increase to mitigate the loss (gain) of surplus from a 10% increase in distance relative to paired-auditor's location. We group samples into four categories based on the distribution of corresponding variables. We exploit two variables: Size and Audit Governance. For example, 25th< <=50th represents that trade-off analysis is conducted using observations between the 25th percentile and 50th percentile of size or audit governance. We use the average of size/audit governance, the average of distance between clients and auditors, and the average of auditor industry expertise for observations in corresponding variable distribution. Variable definitions are in Table 2.

Variables	**Distribution**	**Increase Distance (%)**	**Auditor Industry Expertise (%)**
Size	<=25th	10%	360%
Size	25th < <=50th	10%	115%
Size	50th < <=75th	10%	53%
Size	75th <	10%	5%
Audit Governance	<=25th	10%	81%
Audit Governance	25th < <=50th	10%	89%
Audit Governance	50th < <=75th	10%	120%
Audit Governance	75th <	10%	205%
Audit Fee	2,223	2,282,081	425,750

Table 3.4: Do Clients Get Audits from Worse Auditors because Their Preferred Auditors are Located Farther Away?

This table documents whether clients forgo alternative auditors with better match value but located farther away than paired-auditors because costs of distance outweigh benefits from other auditor characteristics. We perform counter-factual analysis by predicting new equilibrium pairs in a scenario when distance between clients and auditors does not matter. Then, We compare total surplus under the new predicted pairs to total surplus under the actual pairs when distance does not matter. We predict a set of new equilibrium matches following the matching process described in Baccara et al. (2012). Avg. Total Surplus is the average of total surplus for actual client-auditor pairs in the market. Change in Avg. Total Surplus is the average of total surplus of the new predicted pairs less total surplus of actual pairs. Change in Avg. Total Surplus (%) is Change in Avg. Total Surplus divided by Avg. Total Surplus. # of Clients Better Off is the number of clients who have a higher total surplus under the new equilibrium pairs than actual total surplus. # of Clients Worse Off is the number of clients who have a lower total surplus under the new equilibrium pairs than actual total surplus. # of Clients Equal is the number of clients who have a same total surplus under the new equilibrium pairs to the actual total surplus. Tenure Considered? represents whether the counter-factual matching process to find a set of new predicted equilibrium pairs is conducted with considering tenure effect in the surplus calculation. Yes represents with considering tenure effects in matching process and No represents without considering tenure effects in the matching process. Total surplus numbers are in dollars.

	Avg. Total Surplus	**Change in Avg. Total Surplus**	**Change in Avg. Total Surplus (%)**	**# Clients Better Off**	**# Clients Worse Off**	**# Clients Equal**	**Tenure Consid-ered?**
#1	1,351,520	21,920	1.622%	166	55	2,002	Yes
#2	66,030	11,270	17.07%	1,429	315	479	No

Table 3.5: Underserved and Overserved MSAs

This table presents descriptive statistics for underserved and overserved regions. We calculate the Auditor/Client Ratio, defined as the number of auditor offices divided by the number of clients, at the MSA level. We then sort MSAs by Auditor/Client Ratio and denote the 10 MSAs with the lowest (highest) ratios as underserved (overserved). MSA is each MSA's official identification number from the US Census database. # Clients represents the number of clients with headquarters in the corresponding MSA. # Clients w/ BigN represents the number of clients with headquarters in the corresponding MSA receiving audit services from Big N accounting firms. # Client w/ Non-BigN represents the number of clients with headquarters in the corresponding MSA receiving audit services from non-Big N accounting firms. # Auditors represents the number of auditor offices located in the corresponding MSA. # BigN Auditors represents the number of Big N auditor offices located in the corresponding MSA. # Non-BigN Auditors represents the number of non-Big N auditor offices located in the corresponding MSA.

Panel A. Underserved MSAs

MSA	**# Clients**	**# Clients w/ BigN**	**# Clients w/ Non-BigN**	**# Auditors**	**#BigN Auditors**	**#Non-BigN Auditors**	**Auditor Client Ratio**
640	23	14	9	4	2	2	0.174
2080	50	30	20	8	4	4	0.160
7360	81	71	10	12	5	7	0.148
3360	98	63	35	14	4	10	0.143
1600	82	59	23	9	4	5	0.110
7400	113	90	23	10	4	6	0.088
2800	13	8	5	1	1	0	0.077
1123	162	118	44	12	5	7	0.074
5775	53	35	18	1	0	1	0.019
875	21	7	14	0	0	0	0.000

Panel B. Overserved MSAs

MSA	**# Clients**	**# Clients w/ BigN**	**# Clients w/ Non-BigN**	**# Auditors**	**#BigN Auditors**	**#Non-BigN Auditors**	**Auditor Client Ratio**
2680	12	4	8	11	2	9	0.917
8960	11	7	4	7	2	5	0.636
3480	11	10	1	6	4	2	0.545
7160	18	11	7	9	4	5	0.500
1520	17	13	4	8	4	4	0.471
1640	11	7	4	5	4	1	0.455
5000	14	6	8	6	3	3	0.429
1680	19	15	4	8	4	4	0.421
2160	23	17	6	9	4	5	0.391
5945	44	18	26	17	4	13	0.386

Table 3.6: Audit Market Welfare in Underserved and Overserved MSAs

This table presents the total surplus and auditor surplus ratio in under- and overserved MSAs. Underserved and overserved MSAs are defined as in Table 5; all other MSAs are grouped and defined as middle MSAs. Avg. Total Surplus is the average of total surplus for client-auditor pairs whose headquarters (client) and office (auditor) are located in MSAs belonging to the indicated groups. Avg. Auditor Surplus Ratio is the average of auditor surplus ratio for client-auditor pairs whose headquarters (client) and office (auditor) are located in MSAs belonging to the indicated groups. Avg. Distance is the average distance between client headquarters and audit office location. Panel B presents the Spearman correlation between Auditor/Client Ratio and Total Surplus, Auditor Surplus Ratio, Distance, and Audit Fee. The correlation is calculated at the client-auditor pair level. The numbers in parentheses are p-values. Panel C presents the comparison between first-best pairs and actual pairs. For each client, the first-best pair is the client-auditor pair that would provide the client with the highest surplus. The actual pair is the client-auditor pair formed at equilibrium. # of Pairs is the number of clients located in the MSA group. First-Best = Actual is the number of clients whose first-best pair is the same as their actual pair. First-Best =ˆ Actual is the number of clients whose first-best pair differs from their actual pair. Ratio is First-Best =ˆ Actual divided by First-Best = Actual. Avg. Rank Ratio is the relative rank of the actual auditor within the auditor pool for client-auditor pairs where the first-best pair differs from the actual pair. Avg. Diff Total Surplus is the average of total surplus in the first-best scenario minus actual total surplus for client-auditor pairs where the first-best pair differs from the actual pair. Total surplus numbers are in dollars and distance numbers are in thousands of miles.

Panel A.

Client MSA	**Auditor MSA**	**# of Pairs**	**Avg. Total Surplus**	**Avg. Auditor Surplus Ratio**	**Avg. Distance**
Over	Under	3	431,420	0.459	0.586
Over	Over	158	1,245,660	0.490	0.011
Over	Middle	19	950,950	0.442	0.318
Under	Under	605	1,203,130	0.540	0.021
Under	Over	8	719,250	0.466	0.957
Under	Middle	83	824,070	0.434	0.513
Middle	Under	101	1,091,090	0.479	0.295
Middle	Over	91	1,062,460	0.477	0.227
Middle	Middle	1155	1,402,080	0.479	0.078

Panel B.

	Total Surplus	**Auditor Surplus Ratio**	**Distance**	**Audit Fee**
Auditor/Client Ratio	0.013	-0.109	-0.311	-0.045
	(0.733)	(0.006)	(<.0001)	(0.249)

Panel C.

MSA	**# of Pairs**	**First Best = Actual**	**First Best =ˆ Actual**	**Ratio**	**Avg. Rank Ratio**	**Avg. Diff Total Surplus**
Under	696	598	98	0.141	0.159	57,450
Over	180	168	12	0.067	0.139	41,180
Middle	1347	1194	153	0.114	0.156	55,240

Table 3.7: Audit Office Relocation from Overserved MSA to Underserved MSA

This table presents the results of a counterfactual analysis of the impact of relocating auditor offices in overserved MSAs to underserved MSAs. In each iteration, We randomly pick one audit office located in each of the 10 overserved MSAs and relocate it to one of the 10 underserved MSAs (one per underserved MSA). We perform 20 iterations and report their average results. We predict new equilibrium matches following the matching algorithm described in Baccara et al. (2012). Avg. Total Surplus is the average of total surplus for actual client-auditor pairs in under- and overserved MSAs. Avg. Total Surplus New is the average of total surplus for new client-auditor pairs in under- and overserved MSAs that are formed under the counterfactual scenario. Diff. Surplus (%) is Avg. Total Surplus New less Avg. Total Surplus divided by Avg. Total Surplus. Tenure Considered? indicates whether the counterfactual matching algorithm to find new predicted equilibrium pairs considers tenure in its surplus calculation. Yes represents with considering tenure effects and No represents without considering tenure effects. Total surplus numbers are in dollars.

	MSA	**Avg. Total Surplus**	**Avg. Total Surplus New**	**Diff. Surplus (%)**	**Tenure Consid-ered?**
Random Re-location	Under	1,203,130	1,207,180	0.34%	Yes
Random Re-location	Over	1,245,660	1,249,210	0.28%	Yes
Random Re-location	Under	42,160	43,650	3.41%	No
Random Re-location	Over	34,300	35,260	2.73%	No

Table 3.8: Audit Office Entry into a Local Audit Market

This table presents the results of two counterfactual analyses. In Panel A-1 and Panel A-2, We simulate a scenario in which two auditor offices enter the California audit market.

Panel A-1.

All Industry in CA			**SIC 2digit=28 in CA**				
# Clients	**Avg. Total Surplus**	**Avg. Distance**	**# Clients**	**Avg. Total Surplus**	**Avg. Distance**	**#Location Mismatch**	**#Non CA Auditors**
451	995,620	0.081	112	637,810	0.114	3	5

Panel A-2.

Auditor Characteristics					**Outcome**			
	Big N	**Expertise**	**Location**	**Capacity**	**Surplus Change**	**%Surplus Change**	**# Location Mismatch**	**# Non CA Auditors**
#1	N	Average		Average	830,330	1.2%	3	4
#2	Y	Average	Middle of	Average	1,012,400	1.4%	3	4
#3	Y	Average	Auditor Pool	Max	1,626,630	2.2%	3	3
#4	Y	Max		Max	1,903,470	2.6%	3	3

In Panel B-1 and Panel B-2, We simulate a scenario in which the KPMG St. Louis office in Missouri moves to the Las Vegas audit market.

Panel B-1.

GVKEY	**SIC**	**Client Loc**	**Total Surplus**	**GVKEY**	**SIC**	**Client Loc**	**Paired Auditor**	**Total Surplus**
122394	73	St. Louis, MO	1,603,030	178494	73	Las Vegas, NV	Cherry Bekaert LLP Atlanta, GA	506,930
				066261	73		Anton & Chia LLP Newport, CA	185,110

Panel B-2.

GVKEY	**# Clients**	**Client Loc**	**Paired Auditor**	**Surplus**	**Surplus w/ KPMG LV**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
178494	73	Las Vegas, NV	Cherry Bekaert LLP Atlanta, GA	506,930	540	506,930	198,070	395,540	593,010
066261	73		Anton & Chia LLP Newport, CA	185,110	-3,200	185,110	194,300	391,770	589,240

Table 3.9: Total Surplus and Audit Quality

This table presents the test results on the relation between audit quality and client-auditor pair total surplus. We run regressions with three dependent variables: ADA(Absolute Discretionary Accruals), Restatements, and Auditor Change. The main variable of interest is Total Surplus, calculated as the sum of client surplus and auditor surplus estimated using the parameters in Table 2. Distance is defined as the distance between the city level client headquarters location and the corresponding audit office location, calculated using latitude and longitude. Big N is an indicator variable equal to 1 if the audit office is one of the Big N audit offices. Market Value represents a firm's market capitalization. ROA is calculated as net income divided by total assets. Leverage is calculated as total liabilities divided by total assets. Current Ratio is calculated as current assets divided by current liabilities. Quick Ratio is defined as current assets minus inventory divided by current liabilities. ROA_Loss equals ROA multiplied 1 if the client has negative income before extraordinary items and 0 otherwise. ABS(Extraordinary Items) is the absolute value of extraordinary items divided by total assets. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	ADA	**Restatements**	**Auditor Change(t+1)**
Intercept	-2.469***	0.015	0.171***
	(-29.095)	(1.048)	(14.345)
Total Surplus	-0.004**	-0.001**	-0.008***
	(-2.073)	(-2.069)	(-14.544)
Distance	0.104***	0.004	-0.007
	(4.363)	(0.727)	(-1.569)
Big N	-0.134***	-0.002	-0.107***
	(-5.380)	(-0.373)	(-18.938)
Market Value	-0.068***	-0.001	-0.001
	(-12.376)	(-0.609)	(-1.273)
ROA	-0.062***	0.001	0.001
	(-3.083)	(0.470)	(1.108)
Leverage	0.080***	0.001	-0.003***
	(4.052)	(0.616)	(-3.132)
Current Ratio	-0.003	-0.001***	-0.001***
	(-1.274)	(-3.736)	(-2.579)
Quick Ratio	0.646***	0.003	-0.014
	(9.842)	(0.185)	(-1.093)
ROA Loss	0.468***	-0.000	0.006
	(22.625)	(-0.087)	(1.305)
ABS(Extraordinary Items)	0.138*	-0.004	-0.004
	(1.767)	(-1.384)	(-1.191)
Industry Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
No Obs.	34,139	34,139	34,139
Adj. R^2	0.126	0.036	0.093

Table 3.10: Does proximity add value to clients? – Two stage estimation

This table presents the results of the match value function (equation 19) using maximum score estimation. In this estimation, we use six client-auditor characteristics: distance, tenure, Big N, auditor industry expertise, size, and financial condition. Panel A presents first-stage estimation. Panel B shows the estimation results of second-stage estimation after controlling sorting effects. The variable definitions and estimation using maximum score estimator is identical as previous tests. Standard errors are clustered by 2digit SIC industry classification in Panel B.

Panel A. First-stage estimation

Panel A-1. Client

	Point Estimation
Distance	-291.4^
Tenure	1874.8^
Auditor Industry Expertise	-20.6
Big N	-3.3
No. of Pairs	208,397
% of Satisfied	0.9012

Panel A-2. Auditor

	Point Estimation
Distance	-437.5^
Tenure	2762.7
Size	-4.8^
Financial Condition	0.2^
No. of Pairs	208,397
% of Satisfied	0.9012

Panel B. Second-stage Estimation

	Point Estimation	**Std. Dev**
Intercept	0.2636***	(19.7299)
Mkt_cap	0.0257***	(3.7888)
Distance_client	-0.0687*	(1.791)
Tenure_client	-0.0786	(-0.1928)
Auditor Industry Expertise	-0.0133***	(-3.6590)
Big N	-0.0003	(-0.0809)
Size	0.0131***	(5.2039)
Financial Condition	-0.3820***	(-6.9603)
Obs.	29,891	
Adj. R^2	0.0723	

Figure 3.1: Client and Auditor Distribution by State – Auditor/Client Ratios in 2015

This figure displays 2015 auditor/client ratios by state, defined as the number of audit offices divided by the number of client headquarters.

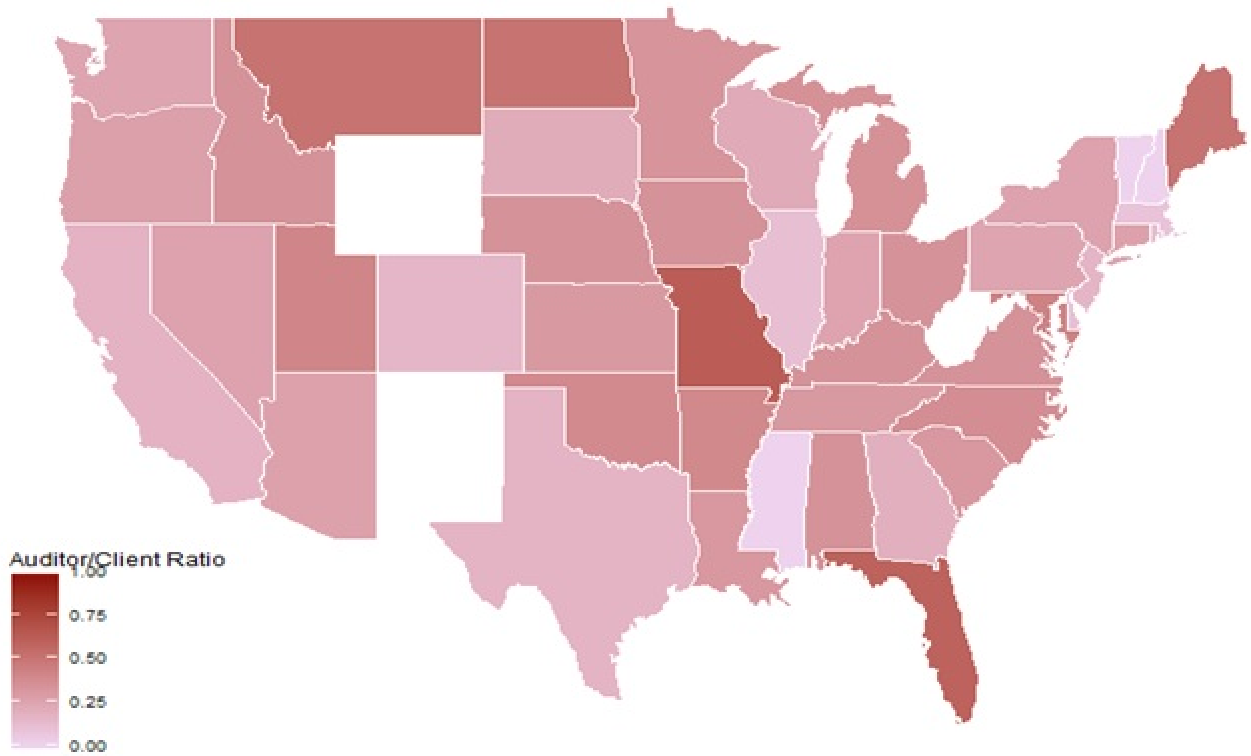


Figure 3.2: Total Surplus by State - Average Total Surplus in 2015

This figure displays the average total surplus for client-auditor pairs by state in 2015. Total surplus is calculated as the audit benefits that clients receive from their paired auditors less the costs that auditors incur in providing audit services to those clients. Total surplus is measured at the individual client-auditor pair level. A detailed explanation of the total surplus and its estimation procedure can be found in Section 4.

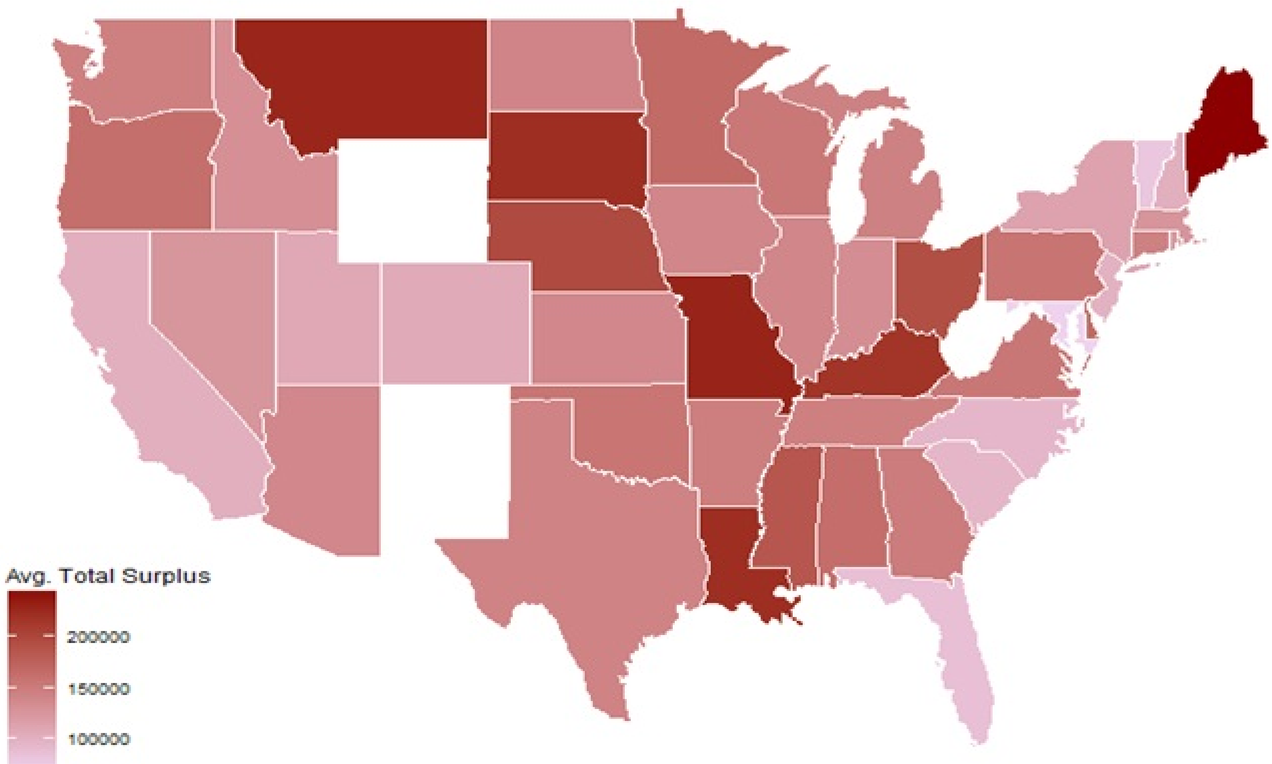


Figure 3.3: Auditor Surplus Ratio by State – Average Auditor Surplus Ratio in 2015

This figure displays the average auditor surplus ratio for client-auditor pairs by state in 2015. The auditor surplus ratio is calculated as auditor surplus divided by total surplus. Auditor surplus is defined as the audit fee that auditors receive from paired clients less the costs that auditors incur in providing audit services to those clients. Total surplus is calculated as the audit benefits that clients receive from their paired auditors less the costs that auditors incur in providing audit services to those clients. Both total surplus and the auditor surplus ratio are measured at the individual client-auditor pair level. A detailed explanation of total surplus, the auditor surplus ratio, and their estimation procedures can be found in Section 4.

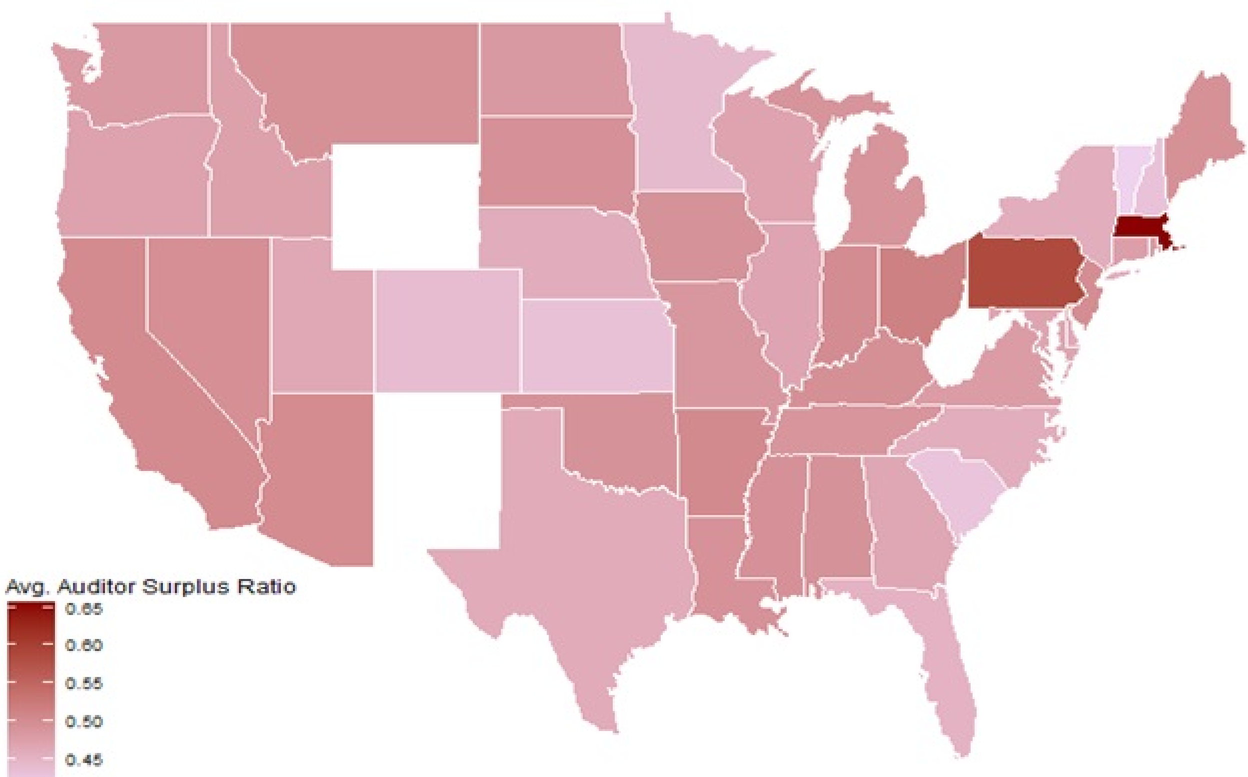


Figure 3.4: Locations of Clients and Auditors in California

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Appendix

Chapter 1

A.1 A Maximum Score Estimator for NTU Matching

A.1.1 Pairwise Stability

The proposed estimator is based on the pairwise stable condition of the matching model. Following Roth and Sotomayor [135], this section introduces the concept of this equilibrium condition. I start with the one-to-one matching.

Let μ be the matching function. Let a and s denote a participant from each side of the market respectively. Let Ω be the set of all possible matching given the participants in the market. We say $\mu(a) = s$ and $\mu(s) = a$ if and only if a and s are matched in A, where $A \in \Omega$,. Note that both a and s can be a null set. If $x = \emptyset$ and $\mu(y) = x$, then y is not paired with anyone in the matching.

Definition: Let $\mu(x) = y$. A matching A is **blocked** by a pair (x', y') if (x', y') is matched in A and there exists a pair (x, y) in A such that x prefers y' than y and y' prefers x than x'.

Definition: A matching A is **(pairwise) stable** if and only if it is not blocked by any matches.

Definition: A matching A is **group stable** if and only if it is not blocked by a coalition of any size.

The scenario is more complex in the many-to-one matching. Still let a and s denote a participant from each side of the market respectively. Now agent as can be matched with multiple agents from the other side of the market. Let $\mu(a)$ denote the set of all s which are matched with a in a matching.

Definition: Matching A has feature of **responsive preference** if for any a, s, s'in $A \in \Omega$ such that $s \in \mu(a)$ and $s' \notin \mu(a)$, a prefers $\{\mu(a)\backslash s\} \bigcup \{s'\}$ than $\{\mu(a)\}$ if and only if a prefers s' than s.

With responsive preference, one can show that a matching is group stable (no group/subset of agents has incentive and feasibility to deviate) if and only if it is pairwise stable. In this case, the many-to-one matching can be viewed as a one-to-one matching with any a with capacity C being replaced by randomly ordered a_1, a_2, ... , a_C, which all have capacity one.

Let $u_a(.)$ and $u_s(.)$ be the utility functions for the two sides respectively. Let $1(.)$ be the indicator function. Then the mathematical condition for pairwise stability can be written as: For some $A \in \Omega$, A is stable if and only if for any pair of matches $[(a,\, s)\,(a',\, s')] \in A$, $1[u_a(s) < u_a(s')] * 1[u_{s'}(a') < u_{s'}(a)] + 1[u_s(a) < u_s(a')] * 1[u_{a'}(s') < u_{a'}(s)] = 0$

A.1.2 Rank Order Property and Maximum Score Estimator

Imposing weak assumptions on the distribution of unobservable quality, Fox [64, 66] proposes maximum score estimators to study the discrete choice model and TU matching game with a so-called "Rank Order Property".

Rank Order Property:

For any given agent w, where w can be from either side of the market, all of her possible partners are captured by a set M_w from the other side of the market. Let X be the set of observable factors of agents and θ be the parameter set. Denote $f(w, m : \theta)$ be the func-

tion of w's deterministic utility from observable factors of a given match between w and m. That is, $u_w(m) = f(w,\, m : \theta) + \omega^{wm}$, where $u_w(m)$ is w's utility of matching with m and ω^{wm} is the unobserved term. For any $m_1, m_2 \subseteq M_w$. The rank order property says, $f(w,\, m_1 : \theta) > f(w,\, m_2 : \theta)$ if and only if the probability of w prefers m_1 is larger than the probability of w prefers m_2.

The intuition is that the unobserved quality does not change the preference determined by observed factors in expectation. The result of Manski [111] indicates that the rank order property holds under the assumption that ω^{wm} has support equal to the real line and an absolutely continuous, independent, and identical distribution across all potential matches in M_w. Goeree et al. [79] and Fox [64] show that a weaker sufficient condition for the rank order property is to assume the unobserved quality follows an exchangeable distribution. For binary choices, i.e. when there are only two possible partners in M_w, Manski [111, 112] shows that it is enough to have a median independence assumption on the distribution for unobservable, i.e. $MED(y|x) = x\beta$. I develop my estimator for NTU matching based on this rank order property.

***Assumption 1**: Define $f_a(a,\, s : \theta_a)$ as the function of a's deterministic utility from a given match between a and s. a's utility of matching with s is given by $u_a(s) = f_a(a,\, s : \theta_a) + \omega_a^{as}$, where ω_a^{as} satisfies the median independence assumption.*

***Theorem 1**: For two matchings A_1 and A_2 such that $A_1 \backslash \{a,\, s,\, a'\, s'\} = A_2 \backslash \{a,\, s,\, a'\, s'\}$, where $a,\, s,\, a'\, s'$ are agents in the market and $\{(a,\, s)\,(a'\, s')\}$ are observed in A_1, $\{(a',\, s)\,(a\, s')\}$ are matched in A_2. With Assumption 1, and if A_1 and A_2 cannot both be stable, the rank order property and the pairwise stability condition indicate that $Pr(A_1\, Stable|X : \theta) > Pr(A_2\, Stable|X : \theta)$ if and only if the following condition does NOT hold:*

CONDITION:$\{f_a(a,\, s : \theta_a) < f_a(a,\, s' : \theta_a)$ & $f_s(a',\, s' : \theta_s) < f_s(a,\, s' : \theta_s)\}$ *OR* $\{f_a(a',\, s' : \theta_a) < f_a(a',\, s : \theta_a)$ & $f_s(a,\, s : \theta_s) < f_s(a',\, s : \theta_s)\}$

Denote $\theta = \{\theta_a, \theta_s)$ *and* $Sta((a,\, s)\,(a'\, s'), \theta) = 1$ *if the above condition does not hold; otherwise* $Sta((a,\, s)\,(a'\, s'), \theta) = 0$*. The above result can be written as* $Pr(A_1\, Stable|X : \theta) > Pr(A_2\, Stable|X : \theta)$ *if and only if* $Sta((a,\, s)\,(a'\, s'), \theta) = 1$*.*

The proof is trivial and therefore omitted. Note that because Theorem 1 requires only two pairs of matched partners to compare the alternative scenario by switching partners, each agent faces a binary choice. Therefore, it is sufficient to have the median independence assumption for the unobservable.

Let Γ denote the set of all possible A_2 for a given A_1. By imposing a specific matching utility model as the following, I can show that for any $A_2 \subseteq \Gamma$, A_1 and A_2 cannot both be stable.

Assumption 2: *Agents* a *and* s *in the match* $(a,\, s)$ *share a total matching utility* U_{as} *with a fixed sharing rule* (e_a, t_a) *determined by* a*. That is* $u_a(s) = (1 - e_a)U_{as} - t_a$ *and* $u_s(a) = e_a U_{as} + t_a$*.*

Theorem 2: *With Assumption 2,* A_1 *and* A_2 *cannot both be stable almost surely (except for the indifference condition).*

Proof: Following the notations in the text, without indifference condition, this indicate the following conditions:

A_1: $(a,\, s)\,(a'\, s')$ stable	A_2: $(a',\, s)\,(a\, s')$ stable
IF a) $u_a(s) > u_a(s')$ & $u_s(a) > u_s(a')$	IF 1) $u_a(s') > u_a(s)$ & $u_{s'}(a) > u_{s'}(a')$
OR b) $u_a(s) > u_a(s')$ & $u_{a'}(s') > u_{a'}(s)$	OR 2) $u_a(s') > u_a(s)$ & $u_{a'}(s) > u_{a'}(s')$
OR c) $u_s(a) > u_s(a')$ & $u_{s'}(a') > u_{s'}(a)$	OR 3) $u_{s'}(a) > u_{s'}(a')$ & $u_s(a') > u_s(a)$
OR d) $u_{a'}(s') > u_{a'}(s)$ & $u_{s'}(a') > u_{s'}(a)$	OR 4) $u_{a'}(s) > u_{a'}(s')$ & $u_s(a') > u_s(a)$

which means that A_1 is stable if and only if any one of the a), b), c) or d) holds; A_2 is stable if and only if any one of the 1), 2), 3) or 4) holds.

Assume both A_1 and A_2 are stable. The only possibilities are {b) & 3)} hold or {c) & 2)} hold. Given that $u_a(s) = (1-e_a)U_{as} - t_a$ and $u_s(a) = e_a U_{as} + t_a$, when $e_a \neq 1 \, or \, 0$, {b) & 3)} gives $u_a(s) > u_a(s')$ & $u_{a'}(s') > u_{a'}(s)$ & $e_a U_{as'} + t_a > e_{a'} U_{a's'} + t_{a'}$ & $e_{a'} U_{a's} + t_{a'} > e_a U_{as'} + t_a$. This form a contradiction of inequality after some simple algebra. When $e_a = 0 \, or \, 1$, it is a contradiction also as its indicating $t_a > t_{a'}$ and $t_{a'} > t_a$.

Same proof goes for {c) & 2)}. QED.

Assumption 2 fits the accelerator admission market as well as many other real-life scenarios, such as the matchings between retail shelf space and whole seller and between real estate broker and buyer. Sørensen [139] is a special case of such setting by restricting e_a and t_a to be the same across all as.

Now I can define the objective function for the NTU matching maximum score estimator. For a given market, researchers observe a realized stable match A.[10] Randomly draw any two pairs of matched agents from A, (a, s) and (a', s'). Denote $C_i = \{(a_i, s_i), (a'_i, s'_i)$ and $C'_i = \{(a'_i, s_i), (a_i, s'_i)$ for each draw i and $i = 1, 2, 3...n$, where n is the size of the sample. Let $G(X)$ be the deterministic part of the total matching utility. So $U_{as} = G(X^{as} : \theta) + \omega^{as}$, where ω^{as} is the unobservable satisfying the assumptions in Theorem 1. With Assumption 2, we can write $f_a(a,\, s : \theta) = (1 - e_a)G(X^{as} : \theta) - t_a$ and $u_a(s) = f_a(a,\, s : \theta) + \omega_a^{as}$, where

[10] This model is also applicable for multiple markets.

$\omega_a^{as} = (1 - e_a)\omega^{as}$. It is easy to see that median independence feature is preserved for ω_a^{as}. Similarly, we get $f_s(a,\, s : \theta) = e_a G(X^{as} : \theta) + t_a$ and $u_s(a) = f_s(a,\, s : \theta) + \omega_s^{as}$. As in Theorem 1, let $Sta(C_i, \theta) = 1$ if and only if $1[f_a(a,\, s : \theta) - f_a(a,\, s' : \theta) < 0|C_i, \theta]1[f_s(a',\, s' : \theta) - f_s(a,\, s' : \theta) < 0|C_i, \theta] = 0$ and $1[f_a(a',\, s' : \theta) - f_a(a',\, s : \theta) < 0|C_i, \theta]1[f_s(a,\, s : \theta) - f_s(a',\, s : \theta) < 0|C_i, \theta] = 0$. Otherwise, $Sta(C_i, \theta) = 0$. The proposed estimator is the following:

$$\bar{\theta} = argmax_\theta \frac{1}{n} \sum_{i=1}^{n} (1[Sta(C_i, \theta) = 1] - 1[Sta(C_i', \theta) = 1]) \qquad (26)$$

Because the proposed estimator takes the observed matching as stable and compares it with a specific neighbourhood of the observed matching, in which no other matching is stable, it allows for the existence of multiple equilibria.

A.1.3. Identification

Following Manski [112] and Fox [64], it is straightforward to see the identification results for cases like "$Pr(a|X) > Pr(b|X)$ if and only if $f(x_a) > f(x_b)$ AND $g(x_a) > g(x_b)$, for some utility functions $f(.)$ and $g(.)$" [11]. The scenario is more complex when one needs to deal with "$Pr(a|X) > Pr(b|X)$ if and only if $f(x_a) > f(x_b)$ OR $g(x_a) > g(x_b)$", as in the case of NTU matching. In detail, the condition in Theorem 1 is equivalent to at least one of the following conditions holds:

- CONDITION A: $\{f_a(a,\, s : \theta_a) > f_a(a,\, s' : \theta_a)$ & $f_a(a',\, s' : \theta_a) > f_a(a',\, s : \theta_a)\}$
- CONDITION B: $\{f_a(a,\, s : \theta_a) > f_a(a,\, s' : \theta_a)$ & $f_s(a,\, s : \theta_s) > f_s(a',\, s : \theta_s)\}$
- CONDITION C: $\{f_a(a',\, s' : \theta_a) > f_a(a',\, s : \theta_a)$ & $f_s(a',\, s' : \theta_s) > f_s(a,\, s' : \theta_s)\}$
- CONDITION D: $\{f_s(a',\, s' : \theta_s) > f_s(a,\, s' : \theta_s)$ & $f_s(a,\, s : \theta_s) > f_s(a',\, s : \theta_s)\}$

[11] See Akkus et al. [6] for an application.

The model cannot be identified without additional information as all four conditions can generate the same matching pattern. For example, while there is no conflict between B and C, these two conditions can indicate totally opposite ranking sequences of the underlying matching utilities. Further, there are two utility functions to be estimated, $f_a(.)$ and $f_s(.)$, but condition A (D) provides no information on $f_s(.)$ ($f_a(.)$).

With an exclusion restriction condition, Tamer [143] proves the identification for the incomplete simultaneous discrete response model with multiple equilibria. Following a similar intuition, if there is a factor $x_a \subseteq X_a$, where X_a is the set of factors from one side of the market, such that x_a has full support on $\mathbb{R}$ conditional on all the other factors in X_a, and if we know $f_s(.)$ is strictly increasing (or decreasing) in x_a, we can show that condition A and/or B (or C and/or D) have to bind for some subset of the observed matches. This is because with full support assumption on x_a, there exist some agents a and a', who are the same except $x_a > x_{a'}$. Then only condition A and/or B can hold for some pairs of matches including both a and a'. This result in turn indicates that $f_a(a,\, s : \theta_a) > f_a(a,\, s' : \theta_a)$ binds, identifying $f_a(.)$. Similarly, the same assumptions on the other side of the market identify $f_s(.)$. The discussion here has similar assumptions and results as in Agarwal and Diamond [4], who show that one can recover parameters of $f_s(.)$ and $f_a(.)$ up to positive monotone transformation assuming full support for $f_a(.)$ and $f_s(.)$ and a sign restriction.

In this paper, we can write $f_a(a,\, s) = e_a U_{as} - t_a$ and $f_s(a,\, s) = (1 - e_a)U_{as} + t_a$. Considering the share e_a and money transfer t_a as the exclusion restrictions, the following theorem shows a sufficient condition for identification:

***Theorem 3**: If* 1) *there is a continuous support for e_a or t_a conditional on X_s and X_a,* 2) *there is a variable $x_s \subseteq X_s$ such that U_{as} has strict monotonic correlation with x_s, and* 3) *x_s has a full support* in $\mathbb{R}$ *conditional on all other variables in X_s, then U_{as} is identified.*

Sketch of Proof: Previous argument shows that the feature of e_a or t_a indicates condition

A and/or B must bind for some subset of matches. Given the functional form, we also know that $f_a(a, s : \theta_a) > f_a(a, s' : \theta_a)$ identifies U_{as}'s variation with s and $f_s(a, s : \theta_s) > f_s(a', s : \theta_s)$ identifies U_{as}'s variation with a. Therefore, the full model identification requires that some subset of matches must satisfy condition B, because condition A only contains information for $f_a(.)$.

Assume U_{as} strictly increase with x_s (the case for strictly decreasing follows the same proof). With the full support assumption as in 3), there exist x_{s1} and x_{s2} such that $x_{s1} > x_{s2}$ for any given a. We then have $U_{as1} > U_{as2}$, which contradicts with condition A. [12] QED.

For e_a, t_a, and x_s, all one needs in practice is to have the support to be rich enough as discussed in Tamer [143]. In the accelerator market, I use the startup age as x_s. In appendix A.2, I show that the startup age is non-trivial to determine the startup value and there is enough variation in this variable after controlling for other observables.

A.1.4 Estimator Asymptotic Property and Non-Random Sample Consistency

To demonstrate its consistency, I show that the proposed estimator is a special case of the method provided by Chernozhukov et al. [34] (CHT hereafter).

I start with defining the data generating process (DGP): In one (or multiple) finite two-sided matching market, denote the sets of the two sides as $\mathbb{A}$ and $\mathbb{S}$ respectively. Given the true parameter β_0 and realized agents types (including both deterministic and unobservable parts), one stable match/equilibrium (which can be different across markets in the case of multiple markets) is formed. Denote this equilibrium (or the set of equilibria for multiple markets) to be A. The set's existence is guaranteed given the market assumptions of finiteness and responsive preference. To form a sample, arbitrarily index all the agents in $\mathbb{S}$ with

[12] If we also know its correlation with U_{as}, x_s can be considered as another exclusion restriction to identify $f_s(.)$ as discussed previously. Here I allow it to be either increasing or decreasing and the identification can still be established.

$i = 1, 2, 3....$ For each s_i, randomly draw s'_i from $\mathbb{S}$ and a_i and a'_i from $\mathbb{A}$ in the same market. Let $C_i^1 = \{(a_i, s_i)(a'_i, s'_i)\}$and $C_i^2 = \{(a'_i, s_i)(a_i, s'_i)\}$. Define $Y_i^1 = 1(C_i^1 \subseteq A)$, meaning that the pair of matches in C_i^1 is observed in A. Similarly, define $Y_i^2 = 1(C_i^2 \subseteq A)$. Since the market is finite, the $Pr(Y_i^1 = 1)$ and $Pr(Y_i^2 = 1)$ have some positive measure in a sample.

Let X denote the observable factors and ε be the unobservable part. Define $Sta(C_i, \beta)$ as in Theorem 1. We can have the following score function:

$$\begin{aligned} Q_n(\beta) = \frac{1}{n} \sum_{i=1}^{n} \{ & 1[Y_i^1 = 1|X, \varepsilon : \beta_0, \mathbf{S}](1[Sta(C_i^1, \beta) = 1|X] - 1[Sta(C_i^2, \beta) = 1|X]) \\ & + 1[Y_i^2 = 1|X, \varepsilon : \beta_0, \mathbf{S}](1[Sta(C_i^2, \beta) = 1|X] - 1[Sta(C_i^1, \beta) = 1|X])\} \end{aligned} \tag{27}$$

The proposed estimator is to find β to maximize the value of Q. In practice, random sampling as described here is inefficient because the chance to sample four agents who form stable matches observed in A is low. Instead, since only those pairs observed in A contribute to the total score, we can randomly draw pairs of matches from A and this brings us to the estimator described previously in 5.3.

Assumption 3*:* *Given $Sta(C_i, \beta_0) = 1$, the equilibrium selection mechanism, $\mathbf{S}$, generates the observed equilibrium, A, with at least the same probability than any other possible equilibrium. i.e. denote the set for all possible stable matching be Λ. For any $A' \subseteq \Lambda$, $Pr(A'\, chosen|\Lambda, Sta(C_i, \beta_0) = 1, \mathbf{S}) \leq Pr(A\, chosen|\Lambda, Sta(C_i, \beta_0) = 1, \mathbf{S})$.*

Assumption 3 makes sure that

$$\begin{aligned} & Pr(A\, stable|Sta(C_i^1, \beta_0) = 1) > Pr(A'\, stable|Sta(C_i^1, \beta_0) = 1) \\ & \qquad \Rightarrow Pr(A\, chosen|Sta(C_i^1, \beta_0) = 1, \mathbf{S}) > Pr(A'\, chosen|Sta(C_i^1, \beta_0) = 1, \mathbf{S}) \end{aligned}$$

So that following Theorem 3, we have

$$Pr(A\, chosen|\mathbf{S}) > Pr(A'\, chosen|\mathbf{S})\, if\; Sta(C_i^1, \beta_0) = 1$$

Following the notation in CHT, I can define the moment function as

$$m_i = (\{1[Y_i^2 = 1|X, \varepsilon : \beta_0, \mathbf{S}] - 1[Y_i^1 = 1|X, \varepsilon : \beta_0, \mathbf{S}]\}1[Sta(C_i^1, \beta) = 1|X]Z_i',$$
$$\{1[Y_i^1 = 1|X, \varepsilon : \beta_0, \mathbf{S}] - 1[Y_i^2 = 1|X, \varepsilon : \beta_0, \mathbf{S}]\}1[Sta(C_i^2, \beta) = 1|X]\}Z_i')'$$

where Z_i is some instrument defined in section 2.2 of CHT. The result of Theorem 1 and Assumption 3 imply that $E_X(\{Pr[Y_i^2 = 1|X : \beta_0, \mathbf{S}] - Pr[Y_i^1 = 1|X : \beta_0, \mathbf{S}]\}1[Sta(C_i^1, \beta_0) = 1|X]) < 0$ and $E_X(\{Pr[Y_i^1 = 1|X : \beta_0, \mathbf{S}] - Pr[Y_i^2 = 1|X : \beta_0, \mathbf{S}]\}1[Sta(C_i^2, \beta_0) = 1|X]) < 0$ by taking expectation over ε.

The score function is equivalent to

$$\begin{aligned} Q_n(\beta) = \frac{1}{n}\sum_{i=1}^{n} \{&(1[Y_i^1 = 1|X, \varepsilon : \beta_0, \mathbf{S}] - 1[Y_i^2 = 1|X, \varepsilon : \beta_0, \mathbf{S}])1[Sta(C_i^1, \beta) = 1|X] \\ &+ (1[Y_i^2 = 1|X, \varepsilon : \beta_0, \mathbf{S}] - 1[Y_i^1 = 1|X, \varepsilon : \beta_0, \mathbf{S}])1[Sta(C_i^2, \beta) = 1|X]\} \end{aligned} \tag{28}$$

which gives $\underset{\beta}{argmax} Q_n(\beta) = \underset{\beta}{argmin} \parallel [\frac{1}{n}\sum_{i=1}^{n} m_i(\beta)]' W^{\frac{1}{2}}(\beta) \parallel_+^2$ with $W(\beta)$ being an identity matrix, where $\parallel [\frac{1}{n}\sum_{i=1}^{n} m_i(\beta)]' W^{\frac{1}{2}}(\beta) \parallel_+^2$ is the proposed estimator in CHT.

Based on the pairwise comparison, the proposed maximum score estimator has the advantage of generating consistent estimation even with a non-randomly selected sample. Based on results of Fox [64], I briefly sketch the intuition here. Assume that the researcher has data on the whole population, $\mathbf{P}$, (or, equivalently, a random sample) with unobservable, the pairwise comparison says $Pr(Y_i^1 = 1|Sta(C_i^1, \theta) = 1, \mathbf{P}) > Pr(Y_i^2 = 1|Sta(C_i^1, \theta) = 1, \mathbf{P})$. With any sample S selected by sampling method M, the pairwise comparison says $Pr(Y_i^1 =$

$1|Sta(C_i^1,\theta) = 1, S) > Pr(Y_i^2 = 1|Sta(C_i^1,\theta) = 1,, S)$. Assume the sampling method M be independent (but can be non-random) of equilibrium selection mechanism $\mathbf{S}$, meaning $Pr(A\, chosen|\Lambda, S) = Pr(A\, chosen|\Lambda, \mathbf{P})$. The probability of obtain S can be written as $Pr(S|\mathbf{P}; M) > 0$. The pairwise comparison generates consistent estimation because:

$$
\begin{aligned}
Pr(Y_i^1 = 1|Sta(C_i^1,\theta) = 1, \mathbf{P} : \beta_0) > Pr(Y_i^2 = 1|Sta(C_i^2,\theta) = 1, \mathbf{P} : \beta_0)\\
\Leftrightarrow & Pr(Y_i^1 = 1|Sta(C_i^1,\theta) = 1, S : \beta_0) * Pr(S|\mathbf{P}; M)\\
> & Pr(Y_i^2 = 1|Sta(C_i^1,\theta) = 1, S : \beta_0) * Pr(S|\mathbf{P}; M)
\end{aligned}
$$

A.2 Value of Startup Age

The empirical estimation requires the normalization of one parameter. Such a parameter cannot associate with a trivial factor, which has no impact on the matching. Also, the associated factor can serve as the exclusion restriction for identification if it has rich enough support conditional on other observables. I choose the factor to be business age, which is defined as the number of years the startup has been founded before joining an accelerator.[13]

Startups that survived for a long time tend to be different from those newly founded, which is reflected as having higher expected value before joining accelerators. For early-stage startups, those with longer operating history are more likely to have an established business model and customer base, which are helpful to attract potential investors. Moreover, their founders are also more likely to have a better idea of how to run the company. However, it is not clear whether the older business fits the accelerator model well. On the one hand, an established startup can gain more as they know what they want and are ready to obtain venture financing. On the other hand, older firms may have accumulated sufficient capital and knowledge, making the accelerator experience less valuable. In general, evidence shows

[13] I use startup age, business age and firm age interchangeably in this paper.

that older graduates from accelerators still have higher survival rates and are more likely to attract venture financing.[14]

The relationship between startup age and its performance is unlikely to be caused by its correlation with founder experiences. Pearson correlation value is at 0.003 with the existence of experienced founder and at 0.091 with average founder age. Similarly, the relationship is not caused by sorting in the market because there is no apparent variation in startup ages across accelerator tiers. In practice, I normalize the business age parameter to the negative and positive one and pick the one that reports the highest matching value. Consistent with the reduced form evidence, positive normalization generates a better score.

A.3 The Announcement of Start Fund in 2011

On January 28, 2011, Yuri Milner and SV Angel announced that their Start Fund would offer all Y Combinator companies \$150K in convertible debt. The terms of this convertible debt offer is general with the following main points [15]:

- Interest rate: higher of 2% or applicable federal rate.
- Maturity date: two years or maturity date of other convertible notes.
- Automatic conversion: on a \$1m equity financing with no conversion discount and no price cap, provided that the transaction documents provide for a right to purchase a pro rata share of future financings.
- Optional equity conversion: on other equity financings with no conversion discount and no price cap.

[14] This evidence is consistent with the increasing trend of average firm age during my data period: 1.58 in 2008, 1.66 in 2009, 1.79 in 2010, and 1.84 in 2011

[15] Source: http://www.startupcompanylawyer.com/2011/01/31/what-are-the-terms-of-yuri-milnersv-angels-start-fund-150k-investment-into-y-combinator-companies/

A.4 Choice of Matching Value Proxy

In Section 1.7, a consistent estimation requires a measure for the match value, which represents the expected firm value at accelerator graduation. Any unbiased proxy for this value is proper, but coarse proxies can lead to higher variance in estimation. An ideal candidate is the startup valuation at graduation. However, such data are rare even for the well-known startups. In this paper, I pick the long-term (five years) survival status to be the proxy. Another candidate is the long-term funding status/amount, but it suffers from a lack of equity information and biases due to survival. With additional data collection, I might also use firm website traffic/media coverage. However, it is not clear that these measures would significantly improve the estimation results.

Alternatively, I can have $Z\delta + \gamma\left[P + Z'\lambda - (X\beta)\right] + e$, where the true matching value is proxied as $U = P + Z\lambda + \upsilon'$, where $E[\upsilon'|P, Z] = 0$. While the second approach has a weaker assumption, these two models generate equivalent empirical estimation with slightly different interpretations.

A.5 CrunchBase Data for Startups Without Accelerators

To show some general difference of startup profiles between accelerator participants and non-participants, I collect a random sample of non-accelerator participants with 7,131 U.S. based technology startups founded from 2003 to 2011 from CrunchBase. The following table shows some key summary statistics.

It is worth noting that the CrunchBase sample tends to suffer a selection bias as more successful startups are more likely to have a record. This bias exists in most available databases for private firms. As a result, it is not surprising to see that about half of the firms obtained venture financing. Based on the Kauffman Firm Survey, a random panel survey for new firms founded in 2003 in the U.S., high-tech startups see about 3% venture funding rate over seven years.

Note: The table shows summary statistics of a random sample of non-accelerator participants with 7,131 U.S. based technology startups founded from 2003 to 2011 collected from CrunchBase. This data is likely to have a selection bias because more successful startups have a higher chance to report their information. According to the Kauffman Firm Survey, a random panel dataset for new U.S. startups founded in 2003, only about 3% of high-tech startups receive venture financing over the seven-year follow-ups. The funding rates are even lower for non-high-tech firms.

	Obs	**Mean**
% of Startup received Venture Financing	7131	50.72%
Average Startup Age @ 1st Venture Financing	3617	3.13
Graduate Degree Founder in Team	7131	40.34%

A.6 Complementary Policy Evaluation Results

This section provides two sets of complementary results to the policy evaluations. Because of market competition, policy interventions in part of the market can potentially impact the whole market. The first part reports the entire market changes of the two subsidies discussed in Section 1.6. The second part provides a set of comparable results under a different equilibrium mechanism.

A.6.1 Whole Market Impacts

The following tables show the percentage changes of firm value and founder factors due to the policy interventions. Taking female founder participation as an example, I calculate the percentage change as the following: denote number of female founders in the baseline as N_f^b

and in the counterfactual as N_f^{cf}. $FemaleFounderChange\% = (N_f^{cf} - N_f^b)/N_f^b$. Neither policy intervention generates a strong impact to unsubsidized accelerator participants.

Note: * indicates within 95% CI. "SH" represents in startup hubs. This table shows the percentage changes concerning firm values and startup factors for each policy interventions based on the simulated benchmark. In this counterfactual, I impose policies to offer equity-free accelerators to entrepreneurs with disadvantages in accelerators. Under these policy interventions, accelerators do not take any equity from the subsidized startups and compensate for the loss, which is the original equity share times the expected startup value at graduation, from the subsidy. As a result, this subsidy changes the preference of startups but not that of accelerators. The first policy called "Gender Subsidy" supports female applicants to Tier 1. The second policy called "Exp Subsidy" assists first-time founders to increase their opportunity to enter Tier 3. The last policy called "T3 Subsidy" aims to help Tier 3 accelerators located outside of startup hubs.

Participants Change	**(Gender Subsidy-Base)/Base**			**(Exp Subsidy-Base)/Base**			**(T3 Subsidy-Base)/Base**	
	Tier 1	**Tier 2**	**Tier 3**	**Tier 1**	**Tier 2**	**Tier 3**	**SH**	**Non-SH**
Firm Value %	0.06%	0.00%	-0.01%	0.01%	0.00%	1.55%*	-0.01%	3.17%*
Female %	-0.19%	0.18%	0.08%	-0.08%	-0.15%	0.13%	-0.08%	0.10%
Inexperienced %	-0.03%	0.01%	0.04%	0.04%	-0.03%	0.04%	0.01%	0.07%
#Startup Outside SH %	0.07%	-0.07%	-0.03%	-0.01%	-0.03%	-0.05%	0.02%	-0.07%

Note: * indicates within 95% CI. "SH" represents in startup hubs. This table shows the percentage changes concerning firm values and startup factors for each policy interventions based on the simulated benchmark. In the second counterfactual, I evaluate the policy interventions to provide a grant of \$150k to startups but do not change the equity funding structure. Compared with the previous approach, this type of policies often involves bigger subsidies because part of the support indirectly goes to accelerators due to the equity share. These grants change the preference of both accelerators and startups. The first policy called "Gender Subsidy" supports female applicants to Tier 1. The second policy called "Exp Subsidy" assists first-time founders to increase their opportunity to enter Tier 3. The last policy called "T3 Subsidy" aims to help Tier 3 accelerators located outside of startup hubs.

Participants Change	(Gender Subsidy-Base)/Base			(Exp Subsidy-Base)/Base			(T3 Subsidy-Base)/Base	
	Tier 1	Tier 2	Tier 3	Tier 1	Tier 2	Tier 3	SH	Non-SH
Firm Value %	0.06%	-0.01%	-0.01%	0.01%	0.00%	2.31%*	-0.01%	4.27%*
Female %	0.25%	0.35%	-0.15%	-0.44%	-0.53%	7.08%*	-0.13%	0.18%
Inexperienced %	-0.08%	-0.03%	0.12%	0.01%	-0.08%	3.52%*	0.01%	0.10%
#Startup Outside SH %	0.16%	-0.05%	-0.06%	0.06%	-0.08%	0.41%	0.02%	-0.09%

A.6.2 Market Dynamics

This section reports the number of startups which join another accelerator from the baseline, and the number of startups which leave the accelerator market due to policy interventions.

The capital injection causes a much higher impact on the equilibrium by moving more startups in the "Gender Subsidy" and "Exp Subsidy". One reason is that the capital injection involves a larger subsidy; another reason is that offering equity-free accelerators only changes the preference of one side of the market and therefore does not change the equilibrium much. Neither policy causes a large change in the "Tier 3 Subsidy".

Note: This table reports the number of startups which change or leave accelerators due to the impacts of offering equity-free accelerators.

		Tier 1		Tier 2		Tier 13	
		Mean	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
Gender Subsidy	Change	0.11	0.35	0.38	0.61	0.16	0.42
	Leave (alone)	0.42	0.61	0.01	0.10	0.01	0.10
Exp Subsidy	Change	0.51	0.76	0.42	0.75	0.26	0.57
	Leave (alone)	0.05	0.21	0.04	0.18	0.68	0.81
Tier 3 Subsidy	Change	0.77	0.87	0.85	0.91	1.39	1.27
	Leave (alone)	0.01	0.10	0.02	0.12	2.23	1.46

Note: This table reports the number of startups which change or leave accelerators due to the impacts of capital injection of USD 150k.

		Tier 1		Tier 2		Tier 13	
		Mean	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
Gender Subsidy	Change	1.16	1.23	0.96	0.93	0.87	0.90
	Leave (alone)	5.46	2.16	0.28	0.57	0.24	0.49
Exp Subsidy	Change	2.10	1.37	1.36	1.16	3.20	1.71
	Leave (alone)	0.58	0.73	0.46	0.71	33.34	4.77
Tier 3 Subsidy	Change	0.89	0.91	1.10	1.00	0.52	0.70
	Leave (alone)	0.01	0.10	0.02	0.12	2.05	1.37

A.6.3 Accelerator Proposing

A caveat of the counterfactual analysis in this paper is that I do not know the equilibrium mechanism of the market, and therefore I cannot replicate the baseline case as realized in the data. In Section 1.6, I construct the equilibrium using Gale and Shapley [72] algorithm with startup proposing, which I argue is likely to be close to being the real case. This section offers a robustness check by providing results using Gale and Shapley [72] algorithm with accelerator proposing. With minor differences, the general patterns are very similar to the case of startup proposing.

Note: * indicates within 95% CI. "SH" represents in startup hubs. This table shows the percentage changes concerning firm values and startup factors for each policy interventions based on the simulated benchmark. I form the matches using Gale and Shapley [72] algorithm with accelerator proposing. In this counterfactual, I impose policies to offer equity-free accelerators to entrepreneurs with disadvantages in accelerators. The first policy called "Gender Subsidy" supports female applicants to Tier

1. The second policy called "Exp Subsidy" assists first-time founders to increase their opportunity to enter Tier 3. The last policy called "T3 Subsidy" aims to help Tier 3 accelerators located outside of startup hubs.

Participants Change	**(Gender Subsidy-Base)/Base**			**(Exp Subsidy-Base)/Base**			**(T3 Subsidy-Base)/Base**	
	Tier 1	**Tier 2**	**Tier 3**	**Tier 1**	**Tier 2**	**Tier 3**	**SH**	**Non-SH**
Firm Value %	0.07%	-0.01%	-0.01%	0.00%	0.01%	1.54%*	0.00%	3.15%*
Female %	-0.13%	0.08%	0.02%	-0.12%	0.00%	0.20%	0.05%	0.09%
Inexperienced %	0.01%	-0.04%	0.01%	-0.04%	0.02%	0.07%	-0.01%	0.06%
#Startup Outside SH %	0.01%	-0.03%	-0.01%	0.02%	0.02%	-0.08%	0.01%	-0.07%

Note: * indicates within 95% CI. "SH" represents in startup hubs. This table shows the percentage changes concerning firm values and startup factors for each policy interventions based on the simulated benchmark. I form the matches using Gale and Shapley [72] algorithm with accelerator proposing. In this counterfactual, I evaluate the policy interventions to provide a grant of $150k to startups but which do not change the equity funding structure. The first policy called "Gender Subsidy" supports female applicants to Tier 1. The second policy called "Exp Subsidy" assists first-time founders to increase their opportunity to enter Tier 3. The last policy called "T3 Subsidy" aims to help Tier 3 accelerators located outside of startup hubs.

Participants Change	(Gender Subsidy-Base)/Base			(Exp Subsidy-Base)/Base			(T3 Subsidy-Base)/Base	
	Tier 1	Tier 2	Tier 3	Tier 1	Tier 2	Tier 3	SH	Non-SH
Firm Value %	0.06%	-0.01%	-0.02%	0.00%	0.01%	2.27%*	0.00%	4.28%*
Female %	0.07%	0.27%	-0.22%	-0.55%	-0.42%	7.21%*	-0.06%	-0.24%
Inexperienced %	0.06%	0.01%	0.02%	-0.01%	-0.04%	3.37%*	0.01%	0.01%
#Startup Outside SH %	0.12%	-0.08%	-0.09%	0.07%	0.04%	0.00%	-0.02%	-0.05%

Chapter 2

B.1 Choice of Matching Value Proxy in 2nd Stage

Proper second stage estimation for funding probability requires a measure for the matching value, which can be interpreted as the expected firm value at accelerator graduation in this project. Any unbiased proxy for value is proper, but those coarse ones can lead to higher variance in estimation. An ideal candidate is the startup valuation at graduation. However, such data is rare even for the well-known startups. In this project, I pick the long-term (five year) survival status to be the proxy. Another candidate is the long-term funding status/amount, but it suffers from a lack of equity information and biases due survival. With additional data collection, I may also use firm website traffic and/or media coverage. However, it is not clear that these measures can significantly improve the estimation results.

Alternatively, I can have $Z\delta + \gamma\left[P + Z'\lambda - (X\beta)\right] + e$, where the true matching value is proxied as $U = P + Z\lambda + v'$, where $E[v'|P, Z] = 0$. Note that these two models generate equivalent empirical estimation with different interpretations, while the second approach is more flexible. As one cannot separately identify δ and $\gamma\lambda$, the second stage result interpretation discussed previously does not hold in the alternative setting. However, it is still valid to form $MF = Z(\delta + \gamma\lambda)$ for the third stage estimation.

Chapter 3

C.1 Differences in inferences drawn from modeling the audit market as a one-sided market vs. a two-sided market

This section illustrates the erroneous conclusions researchers may reach by omitting one side of the audit market when examining audit pricing. Note that the simple illustration provided here offers an intuitive explanation to guide readers but does not provide a comprehensive picture. Therefore, the illustration does not reflect the complex structure of the audit market; rather, it is a thought experiment designed to explain assertions made in this paper.

Suppose there are two clients C1 and C2. C1 values each unit of audit expertise at \$2 and has a governance quality of 15. C2 values each unit of audit expertise at \$2 and has a governance quality of 20. Therefore, a one-sided market model would lead us to conclude that both C1 and C2 place the same value on audit services – i.e., \$2 per unit of audit expertise.

Now, let's incorporate auditor-side characteristics and preferences. Suppose there are two auditors A1 and A2. A1 provides clients with 3 units of audit expertise at a cost of \$6 and requires a minimum client governance quality of 6. A2 provides 5 units of audit expertise at \$9 and requires a minimum governance quality of 19. Thus, the cost of A1's audit service is \$2 per unit of audit expertise (\$6/3 = \$2), while the cost of A2's audit service is \$1.8 per unit of audit expertise (\$9/5 = \$1.8). Because A2's services are cheaper on a per-unit basis, both C1 and C2 would prefer to purchase audit services from A2. However, A2 cannot provide audit services to C1 because C1's governance quality (15) is lower than A2's threshold of 19. Therefore, the client-auditor relationships that will form in this case are (C2, A2) and (C1, A1).

Simply observing this equilibrium outcome, without properly incorporating auditor-side preferences in the formation of equilibrium pairs, suggests that C1 and C2 value audit expertise differently (C1: $2 per unit of audit expertise, C2: $1.8 per unit of audit expertise). In fact, C1 and C2 place the same value on audit expertise ($2 per unit of audit expertise); to avoid an erroneous conclusion, it is essential to consider both sides of the market.

C.2 Explanation of the difficulties of making ex-ante predictions

Let's assume researchers are running an OLS regression by regressing audit fee on a proxy of governance.

$$ln(AuditFees) = a + \beta_1 ClientGovernance + \varepsilon$$

The coefficient on β_1 will be either positive, negative, or zero. Regardless of the outcome, researchers will not be able to disentangle whether the audit benefits, the audit costs, or both are driving the results. Therefore, the conventional approach inherently limits our ability to understand whether and how client governance matters for client- (auditor-) side demand for (supply of) audit services.

For example, if researchers find a positive coefficient for β_1, the result may stem from clients with better governance systems valuing better audit services and thus paying more for such services (e.g., DeFond and Zhang [49], Hay et al. [88]). Alternatively, it may be driven by auditors putting in more effort to provide better audit services in order to avoid higher reputational loss from not properly auditing clients with better governance (e.g., DeAngelo [46]). Alternatively, the positive coefficient might be driven by the combination of the bottom arrows in the client-side prediction and the top arrows in the auditor-side prediction. Overall, the conventional approach does not reveal the economic story behind the β_1 coefficient, which is researchers' ultimate goal.

C.3 Costs and Benefits associated Proximity / Auditor Industry Expertise / Big 4

	Client		Auditor	
	Benefit	**Cost**	**Benefit**	**Cost**
Proximity	- Timelier auditor involvement - Better feed back on internal control system	- Decrease choice sets	- Provide high quality service - Maintain client-auditor relationship - Build reputation	- Decrease choice sets - Personal ties
	Trade-off			
Auditor Industry Expertise **Big 4**	- Higher quality audit service - Capital market benfits	- Unnecessarily high audit requirments	Depends on client characteristics - "Am I capable to provide audit service to a particular client?" - "Does a particular client have high audit risk that may potentially impair my future reputation?"	