How do Large Companies Affect Entrepreneurship: Evidence From Amazon's HQ2 Search

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Abstract

I identify a specific channel (the prospect of getting funded or acquired by large firms) through which entrepreneurship is affected. By exploiting the variation across entrepreneurs' reactions to the two announcements of Amazon's new headquarters (HQ2) search, I find that after the announcement of the 20 finalist cities, new startups that are the potential funding or acquisition targets of Amazon are more likely to be established in one of those 20 cities. After the winning cities were selected, the newly created potential targets of Amazon are more likely to be founded only in the winning cities but not in the losing finalist cities. I also find that there exists a local competition for startups to get funded or acquired by Amazon, which is inconsistent with agglomeration explanation. I present evidence consistent with two possible underlying mechanisms: the synergy benefits from selling out to large firms and the difficulty in obtaining early-stage funding from non-corporate investors.

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1 Introduction

It is well documented that large firms hurt entrepreneurship by employing various entry deterrent strategies.[1] Bunch and Smiley (1992) document that intensive advertising (Comanor and Wilson 1967) and preemptive patenting (Gilbert and Newbery 1982) are used most often by large firms to deter entry. Moreover, large firms' big market power and deep pockets make it hard for startups to compete with them in the product market. Therefore, it is not surprising to see several media outlets blame large businesses for the decline in the startup activities (Buchanan 2015; Casselman 2017).

Given the growing concerns about the impacts of corporate giants on our society as well as the important roles that startups play in job creation and economic growth. (e.g., Decker et al. 2014; Haltiwanger, Jarmin, and Miranda 2013), it is important to have a complete picture of the impacts of large firms on entrepreneurship. In this paper, I study such impacts on entrepreneurship from a different angle–large firms' funding and acquisition activities. Large firms have been very aggressive in funding and acquiring young ventures to bring in innovative ideas, new technology, and talent.[2] However, from the entrepreneurs' perspective, there is little evidence regarding whether these funding and acquisition activities would affect their entry decision. To fill this gap, this paper aims to empirically investigate whether the prospect of getting acquired or funded by large firms has an impact on entrepreneurs (funding/acquisition channel).

Whether the funding/acquisition channel has an impact on entrepreneurs is ultimately an empirical question. On the one hand, entrepreneurs and their startups may benefit from getting acquired/funded by large firms. By selling out to large firms, startups can achieve greater synergy in the product market (Bayar and Chemmanur 2011; Gao, Ritter, and Zhu 2013), and their founders can avoid idiosyncratic risk exposure (e.g., Chen, Miao, and Wang 2010). By accepting equity

[1]The strategic entry deterrents include, for example, limit pricing (e.g., Matthews and Mirman 1983; Kamien and Schwartz 1971), preemptive patenting (Gilbert and Newbery 1982), intensive advertising (Comanor and Wilson 1967), product variety (Schmalensee 1978), predation and reputation (Milgrom and Roberts 1982), and excess capacity (Dixit 1980).

[2]Figure 1 shows that the percentage of startups' funding rounds that involved corporate investors has almost doubled from 12% in 2010 to 21% in 2018. Figure 2 depicts the rapid growth in the number of young startups that were acquired with age less than five years, increasing from 400 deals in 2010 to over 800 deals in 2017.

investment from large firms, startups could also lower large firms' incentives to enter into their markets (Mathews 2006). Besides, risky startups that are difficult to obtain funding from traditional investors may get funded by corporate investors, which are considered having the greater industry knowledge and a higher tolerance for failure (Chemmanur, Loutskina, and Tian 2014). On the other hand, large firms may exploit startups to pursue their strategic goals (Hellmann 2002). If entrepreneurs are worried about the exploitation, then the funding/acquisition channel may not have any effect on them as they prefer to operate as a stand-alone firm and to be funded by non-corporate investors.

To test this specific funding/acquisition channel, however, is quite challenging because startup activities and large firms' funding/acquisition activities could all be affected by some unobserved factors such as technological progress. To overcome this challenge, I use Amazon's HQ2 search to identify this channel. In September 2017, Amazon announced a new headquarters, called Amazon HQ2, and planned to invest over $5 billion and create as many as 50,000 jobs. In January 2018, Amazon announced 20 finalist cities (see Figure 3) for the HQ2 bidding process. In November 2018, Northern Virginia and New York City were both selected for Amazon HQ2 sites. On February 14th, 2019, Amazon surprisingly canceled the HQ2 plan in New York City, leaving Northern Virginia as the final place for Amazon's new headquarter.

Based on Amazon's two announcements (i.e., the 20 finalist cities and the final HQ2 site), I exploit the variation in the reactions of entrepreneurs across various industry sectors. Specifically, based on Amazon's revealed preferences (i.e., past equity investment and acquisition deals), I estimate the probability of getting acquired or funded by Amazon for each newly established startup to identify which startups are Amazon's potential funding/acquisition targets. I then compare the changes in the likelihood of establishing new startups adjacent to the HQ2, before and after each announcement, between the potential and the unlikely funding/acquisition targets of Amazon, which is a difference-in-differences setting with Amazon's likely funding/acquisition targets as the treatment group.

A key assumption underlying this identification strategy is that the geographical proximity matters in M&As and financing transactions, which is documented in previous studies (e.g., Uysal, Kedia, and Panchapagesan 2008; Cumming and Dai 2010). I also find evidence that Amazon is more likely to invest in and acquire Seattle-based startups. Therefore, this local bias allows me to transform the entry problem into a spatial allocation problem of new startups. In other words, if the prospect of getting acquired/funded by large firms affects entrepreneurs, we should expect that new startups that are Amazon's potential funding/acquisition targets are more likely to be established in the HQ2 city.

I find that after Amazon announced the 20 finalist cities, the potential funding/acquisition targets of Amazon are more likely to be founded in one of the 20 finalist cities. After Amazon selected the final HQ2 site, the potential targets of Amazon are more likely to be established only in Northern Virginia or Washington DC but not in the losing finalist cities.[3]

The implication of these findings is twofold. First, for the likely funding/acquisition targets of Amazon, the effect of the new HQ2 sites on them is positive. Second, the increase and the subsequent reversal in the startup activities in the losing finalist cities provide strong empirical support that the positive effect is causal because it is unlikely that there exists a contemporaneous shock, based on which Amazon selected the 20 finalist cities and based on which Amazon's likely targets made the establishment location decisions.

Furthermore, I conduct various analyses to disentangle the funding/acquisition channel from the agglomeration channel. First, I show that after controlling for new startups' industry sectors, the baseline results continue to hold. Moreover, software- or internet-related startups that have a low probability of getting acquired/funded by Amazon do not respond to Amazon's HQ2 search, suggesting that the positive effect is only driven by the potential funding/acquisition targets of Amazon, not by high-tech firms in general. For the agglomeration channel, we might expect that the positive effect applies to a larger group of high-tech firms, not just concentrate on the Amazon's potential funding/acquisition targets.

Second, I present evidence that there is a local competition for startups within a region to be

[3]Washington DC is included because it is geographically very close to Northern Virginia, and New York City is removed because the plan was canceled by Amazon in February 2019.

acquired/funded by Amazon. I find that, within a given area, the number of newly created potential funding/acquisition targets of Amazon is negatively associated with the cumulative number of similar startups that have already been there. This finding is inconsistent with agglomeration explanations such as labor market pooling and knowledge flow because the geographical clustering, implied by the agglomeration, is opposite to this local competition effect.

Third, I examine whether Amazon's likely targets choose to be adjacent to the HQ2 because of the customer-supplier relationship. That is, they simply want Amazon to be their potential customers, which may not have anything to do with this acquisition/funding channel.[4] After controlling for whether a startup is a potential supplier of Amazon, the previous findings for the likely targets of Amazon continue to hold.

Finally, I explore two potential economic mechanisms (synergy and financing constraints) through which the funding/acquisition channel may positively affect entrepreneurship. First, I find that the likely targets of Amazon that were established in 2018 in one of the 20 finalist cities are less likely to be VC-backed startups or to have accepted any external funding from non-corporate investors as of June 2019, compared to the likely targets that were established in non-finalist cities during the same time. This self-selection is consistent with the view that corporate investors have a higher tolerance for failure and the greater industry knowledge (Chemmanur, Loutskina, and Tian 2014), and thus are willing to invest in riskier entrepreneurial firms that other traditional investors are unwilling to fund.

Second, I test whether the likely targets who established in one of the 20 finalist cities are less likely to be Amazon's competitors. Previous studies have shown that if targets and acquirers directly compete with each other in the product market, then the potential synergy would be lower from M&A (e.g., Rhodes-Kropf and Robinson 2008; Hoberg and Phillips 2010; Bena and Li 2014). I find that likely targets of Amazon that were established in 2018 in one of the 20 finalist cities are less likely to be Amazon's competitors, compared to the likely targets that were established in non-finalist cities during the same time. This evidence is consistent with the view that, by selling

[4]For 69 Amazon's deals shown in the Table OA2, about 23% of funding targets, and about 11% of acquisition targets are Amazon's suppliers.

out to large firms, startups can achieve high synergy from economy of scope (e.g., Gao, Ritter, and Zhu 2013).

Although the findings presented so far are specific to Amazon, the effect of the funding/acquisition channel on entrepreneurship is unlikely to be specific to Amazon. Among tech giants, Amazon is probably least active in acquiring and funding startups. For instance, the number of acquisitions made by Google during the last decade is about three times the number of startups acquired by Amazon. Further, the mechanisms through which this funding/acquisition channel positively affects entrepreneurs are unlikely to be very different across tech firms. Besides, although some tech firms are much smaller than Amazon, they are very aggressive in funding and acquiring startups. For example, Twitter's market cap is only about 3% of Amazon's, but Twitter has acquired more startups than Amazon has done. So for relatively smaller tech firms, as long as they are very active in M&A markets and financing transactions, we can also expect a similar effect from them.

Related Literature

Prior literature studying the impacts of large firms on entrepreneurship is mainly about incumbents' strategic entry deterrents to deter potential entrants.[5] Besides the negative impact due to incumbents' strategic entry deterrents, more recent studies find some positive effects of large firms on entrepreneurship. For example, Gompers, Lerner, Scharfstein, et al. (2005) document that large firms that are undiversified with entrepreneurial environments tend to spawn more entrepreneurs. Babina and Howell (2018) document a knowledge spillover effect from corporate R&D to employees by presenting evidence that corporate R&D investment increases employees' likelihood to leave and establish a startup. To the best of my knowledge, this paper is the first study that investigates the impacts of large firms' funding/acquisition activities on entrepreneurship. Thus, the main contribution of this study is to add to our understanding of the relationship between large firms and young ventures by identifying whether large incumbents' funding/acquisition activities could affect entrepreneurs, exploring why startups are affected by this effect, and showing what types of startups are most affected.

[5] See Bunch and Smiley (1992) for a comprehensive review of various entry deterrence strategies used by large firms.

This paper is also related to a large literature on financing constraints and entrepreneurship. In that regard, this paper is most closely related to Aghion, Fally, and Scarpetta (2007), where they show that a country's financial development is important for small startup's entry and post-entry growth but has no or negative effects on large firms' entry. My findings suggest that large firms could be an important complement to financial intermediaries in terms of promoting entry and post-entry growth of small startups.

This paper also contributes to the literature that studies how M&As shape the R&D and innovation activities between large and small firms. (e.g., Phillips and Zhdanov 2013; Bena and Li 2014; Seru 2014; Wang 2018). Phillips and Zhdanov (2013) present theoretical foundation and empirical evidence that large public firms may decide to let small public firms conduct R&D and then subsequently acquire the companies that have successfully innovated. This paper complements their studies by showing how M&A can affect entrepreneurial entry, a prerequisite for innovation by startups.

In broader terms, this paper contributes to the literature on entrepreneurial entry barriers. Many papers have examined how personal wealth, networking, government regulation, tax policy, and local U.S. banking markets affect entrepreneurs' entry decisions (e.g., Klapper, Laeven, and Rajan 2006; Hochberg, Ljungqvist, and Lu 2010; Gentry and Hubbard 2000; Evans and Jovanovic 1989; Cetorelli and Strahan 2006). This paper contributes to this strand of literature by showing that large firms may not purely be entry barriers for small startups due to their funding/acquisition activities.

The rest of the paper proceeds as follows. Section 2 discusses hypothesis development. Section 3 describes the data and discusses empirical design. Section 4 presents the empirical evidence. Section 5 concludes.

2 Hypothesis Development

As discussed earlier, there is a large literature focusing on established incumbents' strategic entry deterrents. Especially for large companies, their deep pockets and big market power can make the entry deterrents very effective. However, unlike the entry deterrence effect, the funding/acquisition channel may be an important linkage for large firms and young startups to collaborate.

Startups are good at creating proof of concepts and detecting emerging and latent demand but are often struggling to scale their businesses. In contrast, large firms' comparative advantages are marketing, distribution, and manufacturing, but they often launch products they can make rather than what customers want.

From large firms' perspectives, they can benefit from the funding/acquisition activities by learning from startups about the new technologies and expose themselves to an entrepreneurial way of thinking (e.g., Telser 1982; Jovanovic and Rob 1989; Chesbrough 2002; MacMillan et al. 2008), especially when their internal innovation deteriorates (Ma 2019). Not surprisingly, corporate investors experience an increase in their innovation productivity (Dushnitsky and Lenox 2005; Ma 2019) and firm values (Dushnitsky and Lenox 2006) after they made equity investments in startups.

From startups' and entrepreneurs' perspective, they could also benefit from the funding/acquisition activities. Compared to independent venture capital (IVC) firms, corporations or their corporate venture capital (CVC) divisions have longer investment horizons, less focus on financial returns, less contingent compensation schemes, and greater industry knowledge.[6] As a result, corporate investors have a higher tolerance for failure (Chemmanur, Loutskina, and Tian 2014), and thus may invest in young entrepreneurial firms that are perceived by IVCs as too risky to fund. Such an expansion of capital supply to would-be entrepreneurs who anticipate financing needs and who are difficult to get funded by IVCs can encourage them to start new businesses (Evans and Jovanovic

[6]These differences are because of the differences in organizational and compensation structures between IVCs and corporate investors. First, IVCs are structured as limited partnerships and usually have a ten-year investment horizon, whereas the investment horizon of corporate investors is not restricted. Second, IVCs focus on financial returns of their portfolio companies, whereas corporate investors mainly want to create strategic value through investing in startups. Third, the compensation structure of IVC fund managers is performance-based, whereas the investment managers of corporations are not compensated based on the financial performance of companies that they invested in.

1989; Samila and Sorenson 2011). In addition, when a startup gets funded by an established incumbent, the equity investment can effectively reduce the incumbents' incentives to enter into the startup's market if the incumbent has not entered yet (Mathews 2006). Therefore, the prospect of getting funded by large incumbents can also have a positive effect on would-be entrepreneurs who are worried that the large incumbents would enter into their markets and directly compete with them.

The prospect of getting acquired by large firms may also positively affect entrepreneurship for several reasons. First, entrepreneurs usually have an undiversified portfolio. Flexible exit options due to large firms' acquisition activities may enable entrepreneurs to exit earlier to avoid idiosyncratic risk exposure, and they are particularly valuable for entrepreneurs who face financing constraints (Chen, Miao, and Wang 2010; Wang, Wang, and Yang 2012). Second, large firms' acquisition activities may also positively affect entrepreneurship if entrepreneurs value the private benefits of control less than the wealth realized by selling out to the large firms (Rossi and Volpin 2004). Last, acquisitions by large incumbents could generate many synergy benefits. Bayar and Chemmanur (2011) provide theoretical foundation that when facing large, dominate firms, startups prefer to be acquired rather than to go public because of greater synergy benefits in product market are high. Gao, Ritter, and Zhu (2013) also find that, compared to going public, entrepreneurs prefer to exit via acquisitions because the large incumbents can help new ventures achieve greater economies of scale and scope and bring new technologies to market faster given their operational expertise, sales force, and distribution channels.

The collaboration between large firms and startups via equity investment and acquisition is also supported by the data. Over the last 20 years, the vast majority of startups have chosen to exit via being acquired rather than going public, as documented by Gao, Ritter, and Zhu (2013). In addition, since 2010, the number of companies going public has been quite stable with an average of about 130, whereas the number of startups that were acquired with age less than five years has doubled from 400 deals in 2010 to over 800 deals in 2017, as illustrated by Figure 2. Figure 1 shows the trends of corporate equity investments in startups. Only 12% of funding rounds, across all stages, involved corporate investors in 2010, whereas 21% of funding rounds have corporate investors in 2018, suggesting a 75% increase. Moreover, this upward trend also holds for early-stage funding rounds (i.e., Seed or Series-A round).

However, there could be dark sides for startups to be acquired or funded by large firms. For large firms, funding or acquiring startups is to create strategic value rather than achieve high financial returns. Therefore, they may be incentivized to exploit the new ventures rather than help them grow, especially when the new ventures are potential competitors of the corporate investors. The first study that investigates this issue is perhaps Hellmann (2002), where the author presents a model in which an entrepreneur may avoid equity investment from CVCs if he or she is worried that CVCs' parent companies may exploit the entrepreneur's new venture to pursue their strategic objectives better.

If indeed this is the concern that most of entrepreneurs have and this concern outweighs the potential benefits from the funding/acquisition channel, then we should expect that large firms' funding and acquisition activities have no effect on entrepreneurs' incentive to startup new businesses as they prefer to operate as a stand-alone firm and to be funded only by non-corporate investors.

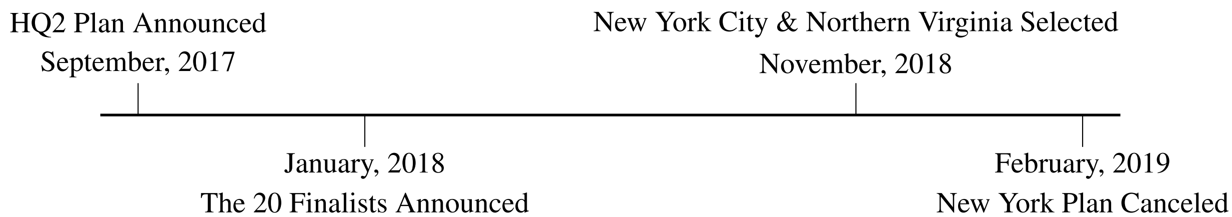
3 Data and Empirical Design

The data for this study are solely from CrunchBase, a new commercial database. According to Kauffman Foundation, CrunchBase is "the premier data asset on the tech/startup world."[7] The advantage of CrunchBase over other commercial databases is the broad coverage due to crowd source, similar to LinkedIn, and data coverage from TechCrunch. Therefore, CrunchBase sample includes startups that are not financed by venture capitals, compared to the data from VentureXpert. In addition, for acquisition data, CrunchBase also contains many small deals that are not covered by SDC. CrunchBase updates its database on a daily basis, which gives me the access to the most

[7] Source: Source: https://www.kauffman.org/microsites/state-of-the-field/topics/finance/equity/venture-capital

up-to-date information about new startups. The data I obtain for this study are updated on June 2019 and include startups founded between January 2000 and June 2019.

3.1 Amazon's HQ2 Search



In September 2017, Amazon proposed a new headquarter, called Amazon HQ2, which attracted 238 proposals from cities or regions in Canada, Mexico and the United States. The HQ2 is expected to invest over $5 billion and create as many as 50,000 jobs. In January 2018, Amazon announced 20 finalists (see Figure 3) to continue the process. These 20 cities or regions are selected based on the following criteria[8]:

- Metropolitan areas with more than one million people
- A stable and business-friendly environment
- Urban or suburban locations with the potential to attract and retain strong technical talent
- Communities that think big and creatively when considering locations and real estate options

In November 2018, Northern Virginia and New York City were both selected for HQ2 sites. On February 14th, 2019, Amazon surprisingly canceled the HQ2 plan in New York City, leaving Northern Virginia as the final place for Amazon's new headquarter.

[8]Source: Source: https://www.amazon.com/b?ie=UTF8&node=17044620011

3.2 Identify Amazon's Funding/Acquisition Targets

To identify what kinds of startups that Amazon is interested in investing or acquiring, I rely on the revealed preference of Amazon (i.e., the past equity investment and acquisition deals). Specifically, by analyzing the characteristics of those deals' targets, I estimate the probability of getting acquired or funded by Amazon based on those characteristics.

The estimation is based on acquisition and investment deals with Northern American targets by Amazon, Amazon Web Services, a subsidiary of Amazon, and the Alexa Fund, the corporate venture capital of Amazon. The sample deals happened between 2007 and 2017. The target firms founded before 2000 are excluded with an emphasis on small deals. The final deals include 35 acquisitions and 35 equity investments. The details of these target companies are in the Table OA3.

CrunchBase provides multiple keywords for each startup's product or service, based on which I extract the keywords that appear in at least two startups' business descriptions. The reason for this requirement is to select technologies or products that Amazon continues to be interested in. For example, to constantly improve the efficiency in its fulfillment centers, Amazon is likely to continue to acquire or invest in robotics companies. I also manually remove some keywords that are too general (e.g., internet, hardware, and consumer electronics). For instance, a video streaming startup may include keywords such as "video streaming", "video", and "internet ". What matters here is "video streaming", and the other two keywords would simply add noise to the estimation process. The goal here is to select the technology or product keywords as specific as possible. For the details of this process, please see Table OA1 in the online appendix section.

The final set of keywords used to estimate the probability of getting acquired or funded by Amazon are shown in Table 1. In total, there are 22 keywords representing a variety of technologies and products such as artificial intelligence, digital media, smart home, and robotics. 16 keywords are extracted from equity investment deals and 18 keywords are extracted from acquisition deals. In addition, for those 16 keywords from equity investments deals, 12 of them also appear in the acquisition targets, suggesting a high overlap in the technologies or products between funding and acquisition targets.

To estimate the probability of being either acquired or funded by Amazon, I use Logit model. The estimation sample includes all the Northern American companies founded between 2000 and 2017 in CrunchBase database, and excludes companies closed or acquired before 2007, given that the deal sample is constructed after 2007.

The resulting predictors and estimation outcomes are presented in Table OA2, with Robotics, Smart Home, and Video Steaming being 3 most powerful predictors. Smart Home is an especially strong predictor with coefficient being 60% larger than second-strongest predictor, Robotics. This is consistent with the prevalence of Amazon's current core product, Alexa, which is a virtual assistant and can be used as the controller of a home automation system.

Moreover, in Table 1, I link each keyword to Amazon's potential competitor and supplier. To identify which keyword is associated with Amazon's suppliers, I searched online for each of the 69 targets to identify which firms are Amazon's suppliers and then assign the keywords of identified suppliers as the supplier keyword in Table 1, the details of which are in Table OA1. To identify competitor keywords, I use Amazon's 10-k, which discloses what types of firms that Amazon considers to be its competitors, the details of which are in section OA.1. I then use the descriptions provided in Amazon's 10-k to identify which keywords are associated with Amazon's competitors.

3.3 Sample Construction

Table 2 shows the distribution of all startups in the CrunchBase database as well as the keyword startups across establishment years. As shown in the Table 2, since 2010, the percentage of keyword startups out of all the startups in the CrunchBase database has been quite stable, around 41%. Table 3 shows the summary statistics for keyword startups that were founded between 2014 and 2019. The average probability of getting acquired or funded by Amazon is about 0.05%. About 20% of the startups in this sample have "internet" in their business descriptions and 40% of the startups have "software" in their business descriptions. In addition, 24% and 26% of the startups in this sample are Amazon's potential suppliers and competitors, respectively. Last, within this sample, from 2014 to 2019, 34% of the startups were established in one of the 20 HQ2 finalist cities and 1.4% were established in Northern Virginia or Washington DC.

3.4 Empirical Design

Based on the announcement of 20 HQ2 finalist cities and the announcement of the final decision, I exploit the variation across entrepreneurs' reactions in terms of the location choices of their newly created startups. Specifically, for each Amazon's announcement, I compare the changes, before and after the announcement, in the likelihood of establishing new startups adjacent to Amazon's HQ2 between the likely funding/acquisition targets of Amazon and the unlikely funding/acquisition targets of Amazon. The resulted OLS and Logit difference-in-differences regressions with continuous treatment variable $Prob_{it}$ for each announcement (the parentheses in the equations below correspond to the final HQ2 site announcement) are as follows:

$$HQ2_{it}(NV\&DC_{it}) = \alpha_t + \beta Prob_{it} \times Y_{2018} + \theta Prob_{it} \times Y_{2019} + \gamma Prob_{it} + \varepsilon_{it} \tag{1}$$

$$Pr[HQ2_{it}(NV\&DC_{it}) = 1|\mathbf{X_{it}}] = \frac{exp(\alpha_t + \beta Prob_{it} \times Y_{2018} + \theta Prob_{it} \times Y_{2019} + \gamma Prob_{it} + \varepsilon_{it})}{1 + exp(\alpha_t + \beta Prob_{it} \times Y_{2018} + \theta Prob_{it} \times Y_{2019} + \gamma Prob_{it} + \varepsilon_{it})} \tag{2}$$

,where $HQ2_{it}$ is a dummy variable that is equal to one if newly created startup i in year t is founded in one of the 20 Amazon HQ2 finalists, $NV\&DC_{it}$ is a dummy that is equal to one if newly created startup i in year t is founded in Northern Virginia or Washington DC,[9] a_t is the establishment year fixed effects, $Prob_{it}$ is estimated probability of getting either invested or acquired by Amazon for startup i founded in year t, Y_{2018} is an indicator if it is the year 2018, Y_{2019} is an indicator if it is the year 2019, and ε_{it} is the error term.

[9]Northern Virginia includes Arlington County, Fairfax County, and Alexandria city. Washington DC is included because it is adjacent to Northern Virginia.

3.5 Identification Assumptions

The first assumption is local bias, which has been shown in various financial phenomena, such as bank lending (e.g., Petersen and Rajan, 2002), analyst coverage (Bae, Stulz, and Tan 2008), and fund managers stock picking (Coval and Moskowitz 1999, 2001). In the context of investment in startups, Cumming and Dai (2010) find that VCs consistently exhibit significant local bias and that local ventures are more likely to have successful ultimate exits. Same local bias also exhibits in M&A deals. Uysal, Kedia, and Panchapagesan (2008) find that acquirer returns in local transactions are more than twice that in non-local transactions.

The well-documented local bias can be attributed to three reasons. First one is local synergies, which might occur, for example, in terms of transport costs between production sites, common inventories management, or common use of buildings and utilization of machinery. Second one is monitoring. Presumably, increasing distance could impose additional monitoring costs. And the last one is information advantage, especially for "soft information", which may be getting harder and harder to acquire as the geographic distance increases.

Table 4 shows that Amazon is not an exception. In columns (1) and (2), the coefficient on the variable, Seattle, is positive and statistically significant at 1% level, indicating that Amazon is more likely to fund startups that were established in Seattle where Amazon's current headquarters is located. In columns (3) and (4), Amazon is shown to be more inclined to acquire Seattle-based startups. Nor surprisingly, in columns (5) and (6), I find that this local bias is stronger for the startups that have a high probability of getting acquired or funded by Amazon.

The other identification assumption is that subsidies offered by local governments are not specifically in favor of the likely funding/acquisition targets of Amazon. This assumption is plausible for two reasons. First, most of the cities offer subsidies directly to Amazon in the form of tax incentives (Leroy 2018). Second, even if some subsidies may have a spillover effect such as infrastructure improvement, it is unlikely that the spillover effect depends on whether the company is an Amazon's likely target or not because the group of Amazon's likely targets is quite diverse (including business services, personal services, manufacturers, and retailers, as shown by the keywords from Table 1).

4 Evidence

In this section, I first show the graphs comparing the reactions to Amazon's two announcements between the likely funding/acquisition targets of Amazon and the unlikely targets of Amazon, which also has the implications for whether there is any omitted variable issue (i.e., a contemporaneous, unobservable shock that affects both Amazon and Amazon's likely targets). I then presents the results of difference-in-differences with the Amazon's likely funding/acquisition targets as the treatment group. Last, I examine the potential mechanisms through which Amazon's announcements affect entrepreneurs' decisions for the locations in which they establish their startups.

4.1 Suggestive Evidence

Panel A of Figure 5 plots the location choice of of newly created startups for each year for treatment and control group from 2014 to the first half of 2019. The treatment group includes startups with $Prob_{it}$ in the top ten percent for each year, and the control group contains the remaining 90% of newly established startups for each year. Prior to the announcement of 20 HQ2 finalist cities, for the control group, the percentage of newly created startups choosing one of HQ2 cities to operate has been growing steadily, from 32% in 2015 to 34% in 2017. For the treatment group, the trend is parallel to the trend of the control group. The percentage of new startups choosing to establish in one of the 20 finalist cities has also been growing steadily, from 31% in 2015 to 32% in 2017.

After the 20 finalist cities were announced in January 2018, this percentage of treatment group went up to over 38% in 2018, indicating a 19% relative increase. Moreover, the increase in 2018 reversed in 2019 after Northern Virginia and New York City were officially announced for the HQ2 sites. This suggests that it is unlikely that there is any contemporaneous, unobservable shock (omitted variable issue) that affects both Amazon's decision of selecting those 20 finalist cities and the decisions of Amazon's likely targets to establish in one of the 20 finalist's cities. If there is such an omitted variable, the trend should not reverse after other 18 cities were excluded for the HQ2 sites. In addition, 20 HQ2 finalist cities were actually more popular among the unlikely funding/acquisition targets than the likely targets, as shown in Figure 5 .

Figure 6 plots the percentage of newly created startups that were established in either Northern Virginia or Washington DC from 2014 to the first half of 2019. Amazon officially selected Northern Virginia and New York City for HQ2 sites in November 2018 and canceled New York plan in February 2019. For the group of the likely targets (the treatment group), Figure 6 shows that the first half of 2019 experienced a significant increase in the the percentage of entrepreneurs choosing either Northern Virginia or Washington DC to start their new businesses. Specifically, 2% of startups from treatment group founded in either Northern Virginia or Washington DC in 2018 and it increased to about 7% in the first half of 2019, representing an about 350% relative increase. For the group of the unlikely targets (the control group), however, about 1.5% of newly established startups were founded in either Northern Virginia or Washington DC from 2015 to 2018 and that percentage even decreased in the first half of 2019 to about 0.5%.

In addition, for the treatment group, after Amazon announced the 20 finalist cities, there was not a significant increase in the percentage of newly created startups founded in Northern Virginia or Washington DC, which is somewhat surprising given Northern Virginia and Washington DC are both the finalist cities. The main reason could be that AWS, a Amazon's subsidiary with an annual revenue of $25.6 billion in 2018, announced in May 2017 that it would choose Northern Virginia over Texas and Washington state for its new east coast headquarters.[10] Thus, people may believe that it is less likely for Amazon to build another headquarters in the same region. This also explains a significant increase, from 1% in 2016 to 2% in 2017, in the percentage of new startups founded in Northern Virginia or Washington DC in 2017.

[10]Source:https://www.geekwire.com/2017/amazon-web-services-planning-new-east-coast-campus-northern-virginia/

4.2 Main Findings

4.2.1 Announcement of the 20 finalist cities

Table 5 presents the results of difference-in-differences regressions specified in equation (1) and (2) for the announcement of the 20 finalist cities. The startups in the sample were founded between 2014 and 2019. The results are consistent with what we observe in Figure 5 . The coefficients on the interaction term $2018 \times Prob$ across all specifications are statistically positive at 1% significance level. Moreover, the coefficients on on the interaction term $2019 \times Prob$ are negative and statistically insignificant, indicating the reversal of startup activities for the likely targets of Amazon in the losing finalist cities. As for the economic significance, an one standard deviation increase in the probability of getting acquired or funded by Amazon leads to about 4% higher chance to establish in one of the 20 finalist cities as indicated by the column (4) of 5.[11]

The coefficient on *Prob* is negative and statistically significant for all specifications, suggesting that unconditionally startups with a high probability of getting acquired and funded by Amazon are more in favor of non-HQ2 cities. The coefficient on *Year* 2018 (not shown in the table), which measures the effect for the startups with least likelihood of being acquired or funded by Amazon, is roughly positive across different specifications. It is worth highlighting that startups with the least chance of being acquired or funded by Amazon does not necessarily mean that they are potential competitors to Amazon because their businesses could be simply unrelated to Amazon's businesses. However, one implication associated with this finding is that Amazon HQ2 event does not generate a substitution effect. Wang (2018) documents this effect by showing that entrepreneurs who are also inventors tend to cater to acquirers if acquirers' market structures are concentrated. The finding here suggests that it is unlikely to see an entrepreneur who used to plan to start a biotech firm now suddenly starts a robotics firm with an aim of getting acquired or funded by Amazon.

[11] One standard deviation of Prob is 0.2%, the sample average of the startups founded in one of the 20 finalist cities is 0.33, and the coefficient on $2018 \times Prob$ is 6.8. Therefore, 4% is calculated as $0.002 \times 7/0.34 = 4\%$

4.2.2 Announcement of the final HQ2 site

Table 6 presents the findings of difference-in-differences regressions specified in equation (1) and (2) for the announcement of the final HQ2 site. The coefficients on the interaction term $2019 \times Prob$ across all specifications are positive with significance level ranging from 1% to 10%, which is consistent with Figure 6. As for the economic significance, an one standard deviation increase in the probability of getting acquired or funded by Amazon leads to about 15% higher chance to establish in either Northern Virginia or Washington DC in 2019 as indicated by the column (4) of 6.[12]

The coefficients on the interaction term $2018 \times Prob$ across all specifications are positive but statistically insignificant. This may reflect people's belief that Northern Virginia or Washington DC have a lower chance than other finalist cities to be chosen as the final site for HQ2, which is supported by the betting odds from Paddy Power (see more details in Table 8). On January 19, 2018, the next day of the announcement of Amazon's 20 finalist cities, Paddy Power publishes the odds of each finalist city to be chosen by Amazon, in which Northern Virginia was ranked in the lowest group with an odds of 20/1, suggesting a probability of 1/21 to be chosen by Amazon.

4.3 Local Competition for Getting Acquired or Funded by Amazon

For startups that locate near large firms' headquarters, although the local bias discussed earlier increases their chance to be acquired or funded by those large firms, this section presents a countervailing effect, local competition. That is, the number of similar acquisition/funding targets within an area decreases the target's chance to be acquired/funded. I present empirical support to this local competition effect and discuss its important implications for agglomeration as well as why some startups take a chance to bet on one of the 20 finalist cities to be selected by Amazon rather than go to Seattle (Amazon's HQ1 location).

[12] One standard deviation of Prob is 0.2%, the sample average of the startups founded in one of the 20 finalist cities is 0.014, and the coefficient on $2019 \times Prob$ is 1.05. Therefore, 15% is calculated as $0.002 \times 1.05/0.014 = 15\%$

4.3.1 Evidence of Local Competition

Table 7 presents the evidence of the local competition effect specific to Amazon. I count the cumulative number of potential targets of Amazon (top 10% in terms of the estimated probability) established in a given MSA area during two time windows, 2010 - 2017 and 2014 - 2017. The dependent variable is the number of potential targets of Amazon (top 10% in terms of the estimated probability) that were founded in each MSA area in 2018. Across all of the four specifications in Table 7, the coefficients on the cumulative number of potential targets that were established before 2018 are negative and statistically significant at either 10% or 1% significance level, suggesting that there is a local competition for the targets within a MSA area to be acquired/funded by Amazon.

Another evidence for the local competition is shown in the Figure 8. Seattle, as the location of Amazon's HQ1, has been experiencing a decline in the number of the potential targets established there since Amazon announced the 20 finalist cities. And this decline is statistically significant at 5% significance level. If there is no local competition effect, we should not expect any effect on the 20 finalists given the uncertainties for them to be chosen by Amazon. The fact that we see more potential funding/acquisition targets of Amazon that were established in one of the 20 finalist cities and the less in Seattle after the announcement in 2018 is consistent with the local competition effect in the sense that there are already many potential targets established in Seattle, which is sown in the Figure 4.

In addition, Paddy Power, a betting website, published the betting odds for each of the 20 finalist cities to be chosen by Amazon as the final HQ2 site on January 19, 2018, the next day of the announcement of the 20 finalist cities by Amazon. Based on those probabilities from Paddy Power, Table 7 shows that if we exclude Seattle, the coefficient on the probability of each MSA area to be chosen by Amazon is positive, indicating that a higher chance for a city to be chosen as the final HQ2 site leading to more potential Amazon's targets to be established there in 2018. Interestingly, if we include Seattle, the coefficient on the probability becomes insignificant. This is because Seattle is an extreme outlier in this regression. Seattle has a probability of one while it has been experiencing a decline in the number of the potential targets established there since

Amazon announced the 20 finalist cities. Overall, the results based on Paddy Power's betting odds are consistent with the positive effects I document in Table 5.

4.3.2 Agglomeration

Labor pooling, knowledge flow, and customer-supplier are considered to be three most important forces in industrial agglomeration, which goes back as early as Marshall (1920). It is possible that the huge investment in the HQ2 would enlarge talent pool, improve knowledge flow, and increase the chance of a local firm becoming a supplier of Amazon, all of which could attract the potential funding/acquisition targets to be established in the HQ2 city. Therefore, the positive effects may also be driven by the agglomeration channel. To disentangle the funding/acquisition channel from the agglomeration channel, I conduct various analyses to provide suggestive evidence.

First, the evidence of the local competition discussed above is inconsistent with the agglomeration. The nature of agglomeration is geographical clustering, which is opposite to the local competition. The results in 7 show that many similar Amazon's potential funding/acquisition targets established in a given area would discourage newly established potential targets to be established in the same area. However, from agglomeration's perspective, more firms in a given area should be able to attract more similar firms, which is what happened in Silicon Valley area.

Second, since the vast majority of Amazon's businesses are related to software and internet, the talent pool and knowledge flow would be improved for all software or internet related startups, not just for the likely funding/acquisition targets of Amazon. To test this, column (3) and (6) in Table 5 presents the results of difference-in-differences regressions specified in equation (1) and (2) for the announcement of the 20 finalist cities. After controlling for the software and internet, the coefficients on $2018 \times \textit{Prob}$ are still positive and statistically significant. Second, the coefficients on $2018 \times$ Internet and $2018 \times$ Software in both columns (3) and (6) are almost zero and insignificant. Column (3) and (6) in Table 6 show the similar pattern. After controlling the software and internet, the coefficients on $2019 \times \textit{Prob}$ are still positive and statistically significant. And the coefficients on $2019 \times$ Internet and $2019 \times$ Software in both columns (3) and (6) are almost zero and insignificant. Together, these results suggest the positive effects on the likely targets of Amazon are not driven by whether a startup is a internet (software) related.

These findings are inconsistent with the possibility that the likely targets of Amazon choose to get closer to the HQ2 because of larger talent pool or better knowledge flow due to the huge investment in the HQ2. Since Amazon is certainly a software and internet related company, we should expect the talent pool and knowledge flow would be improved for all software or internet related startups. In other words, if these two are the driving forces, we should not expect that the effect is constrained in a specific group (i.e. the likely funding/acquisition targets of Amazon).

4.3.3 Customer-Supplier Relationship

As discussed above, talent pool and knowledge flow are unlikely to be the reasons for the likely target of Amazon to be established in one of the 20 finalist cities after the announcement. Here I examine another important driving force in the industrial agglomeration literature, which is customer-supplier relationship.

It is possible that the findings discussed earlier can be attributed to customer-supplier relationship since being closer to Amazon may have a higher chance to become a supplier of Amazon. Therefore, according to this explanation, those startups choosing to be adjacent to Amazon may not have anything to do with the anticipation of getting funded or acquired by Amazon. To examine this alternative alternative explanation, I first identify what types of Amazon's likely funding/acquisition targets are Amazon's suppliers. Based on the 69 funding/acquisitions deals of Amazon during 2009 - 2017, I manually searched on Google to identify who are the suppliers of Amazon. As shown in Table OA3, 23% of equity investment targets and 11% of acquisition targets are Amazon's suppliers. I then use these suppliers' keywords, as shown in Table 1 as the identifier for Amazon's potential suppliers.

To test this, columns (1) and (2) in Table 9 present the results of difference-in-differences regressions specified in equation (1) and (2) for the announcement of the 20 finalist cities, and more importantly the specifications in columns (1) and (2) control for the same difference-in-differences setting for whether a startup is Amazon's potential supplier. First, after controlling the supplier status, the coefficients on $2018 \times \textit{Prob}$ are still positive and statistically significant. Second, the coefficients on $2018 \times$ Supplier in both columns (1) and (2) are negative and statistically significant at 10%, suggesting that the effect of the announcement of the 20 finalist cities on potential suppliers is even negative. Columns (3) and (4) in Table 9 show that after controlling the supplier status, the coefficients on $2019 \times \textit{Prob}$ are still positive and statistically significant. And the coefficients on $2019 \times$ Supplier and in both columns (3) and (6) are almost zero and insignificant. Together, these results suggest that it is unlikely that the reason that the likely targets of Amazon established in one of the 20 finalist cities in response to the Amazon's finalist announcement is because they want to be Amazon's suppliers.

4.4 Possible Mechanisms

4.4.1 Financing Constraints

In Table 11, conditional on startups that were established in one of the 20 finalist cities between 2015 and 2018, I examine whether the likely funding/acquisition targets of Amazon that established in one of the 20 finalist cities are less likely to obtain early-stage funding after Amazon announced those 20 cities. The dependent variable in Panel A is VC-backed that is equal to one if a startup accepted equity investment from a VC firm as of June 2019. For the sample of the 20 finalist cities, the coefficients on interaction term $2018 \times \textit{Prob}$ is negative and statistically significant at 1% level while the coefficients on the term *Prob* is positive and statistically significant at 1% level. However, as a comparison, for the sample of other cities in Northern America the coefficients on interaction term $2018 \times \textit{Prob}$ is insignificant.

The implications of these results are two fold. First, unconditionally the likely targets of Amazon in one of 20 finalist cities are more likely to get funded by VC firms but after Amazon selected those 20 cities as the finalist, the likely targets of Amazon are less likely to have accepted any equity investment from VC firms. Second, the effect of Amazon's announcement of the 20 finalists on its funding/acquisition target, shown in Table 5, are mainly driven by non-VC-backed startups.

Panel B extends the equity investment from VC firms to any form of external funding from non-corporate investors such as angel investors, but does not include bank lending. Qualitatively, the results are exactly same as those in Panel A. Together, the results from both Panel A and B suggest that the increase in the startup activities in the 20 finalist cities are driven by Amazon's likely funding/acquisition targets that are difficult to obtain external early-stage funding from non-corporate investors.

This finding could have two interpretations. First, it could mean that those startups face financing constraints. Alternatively, it may have nothing to do with financing constraints, but simply indicates that those startups lack growth opportunities or are well self-funded and thus do not need more funding. To disentangle these two interpretations, in Table 12, I look into whether the likely funding/acquisition targets of Amazon that established in one of the 20 finalist cities after the announcement are more likely to be founded by non-local entrepreneurs. The dummy variable *Local* is equal to one if the founder or one of the co-founders of a startup is a local entrepreneur. A local entrepreneur is defined as either went to a college or had a previous job in the same city as the current startup's establishment location. Across all specifications, the coefficients on the interaction term, $2018 \times Prob \times Local$, are negative and statistically significant at 5% level, suggesting that more vibrant startup activities in the 20 finalist cities are driven by Amazon's likely funding/acquisition targets that were established by non-local entrepreneurs.

Non-local entrepreneurs, compared to locals, have disadvantages in terms of the access to the funding from local financiers such as banks and VCs (Michelacci and Silva 2007) and presumably have extra switching costs to move to other places. Therefore, lacking growth opportunities is unlikely to be the case because the extra cost of being a non-local entrepreneur is not justified if there is no growth potential. Together, these findings are consistent with the view that corporate investors have a high tolerance for failure (Chemmanur, Loutskina, and Tian 2014) and thus are willing to invest in risky entrepreneurial firms.

4.4.2 Synergy Benefits

Previous studies have shown that if targets and acquirers directly compete with each other in product market, then the potential synergy would be lower from M&A (e.g., Rhodes-Kropf and Robinson 2008; Hoberg and Phillips 2010; Bena and Li 2014). This provides a setting to indirectly test if synergy is another reason that the prospect of getting acquired/funded by large firms can positively affect entrepreneurship.

In Table 10, I examine whether the likely funding/acquisition targets of Amazon that established in one of the 20 finalist cities after the announcement are less likely to be Amazon's competitors.[13] I find that likely targets of Amazon that were established in 2018 in one of the 20 finalist cities are less likely to be Amazon's competitors, compared to the likely targets that were established in non-finalist cities during the same time. Specifically, in Table 10, for the sub-sample of the 20 finalist cities, the coefficients on interaction term $2018 \times Prob$ is negative and statistically significant at 1% level while for the sub-sample of other cities in Northern America the coefficients on interaction term $2018 \times Prob$ is positive but insignificant.

This evidence is consistent with the view that selling out to large, dominate firms generate greater synergy benefits (Bayar and Chemmanur 2011), and is also consistent with the empirical evidence that compared to going public, entrepreneurs prefer to exit via acquisitions because the large incumbents can help new ventures achieve greater economies of scale and scope and bring new technologies to market faster given their operational expertise, sales force, and distribution channels (Gao, Ritter, and Zhu 2013).

4.5 Robustness and Falsification Tests

In this section, I show that the main results from difference-in-differences regressions in Table 5 and Table 6 are robust.

In Table OA4 and Table OA5, I examine whether the main findings from Table 5, Table 6, and

[13] Amazon explicitly describes what types of companies are its competitors in its 10-k. For more details, please see Appendix OA1.

Table 9 are sensitive to the sample period. Instead of 2015 - 2019, I use a shorter time window in Table OA4 and Table OA5, which is from 2017 to 2019. Compared to the sample period of 2015 - 2019, shorter time window do not change the main findings.

In Table OA6 and Table OA7, I examine if the main findings from Table 5, Table 6, and Table 9 are robust to different control groups. In Table 5 and Table 6, any startup that has a low probability of getting acquired or funded by Amazon is effectively in the control group. In Table OA6 and Table OA7, I restrict the sample to all the startups that at least have one keyword from Table 1. As shown in Table 2, this sub-sample accounts for about 40% of startups in the full sample. For this sub-sample, the effective control group includes the startups that have similar characteristics to the startups that were acquired by Amazon or funded by Amazon but have a low probability of getting acquired or funded by Amazon, relative to other startups within this group. As shown in the Table OA6 and Table OA7, the results continue to hold if the control group is changed. This result implies that using the probability of getting acquired or funded by Amazon is robust way to split the control and the treatment group and is not sensitive to the types of startups in the control group.

5 Conclusion

This paper aims to add to our understanding of how large incumbents affect entrepreneurship by identifying a specific funding/acquisition channel through which entrepreneurship is affected. By using Amazon's HQ2 search as a source of identifying variation, I show that only the likely funding/acquisition targets of Amazon are more likely to be established in the HQ2 cities. High-tech, especially software- and internet-related, startups do not respond to the new HQ2 site of Amazon. Moreover, the comparison between the losing and the winning finalist cities provides strong support for the causal interpretation of the positive effect. Because of well-document local bias, these findings identify that the prospects of getting acquired or funded by Amazon can have a positive impact on the NPV of Amazon's potential funding/acquisition targets. Moreover, the effect is particularly strong for startups that face financing constrains and do not directly compete with Amazon.

Although the findings are specific to Amazon, the effect of the funding/acquisition channel on entrepreneurship is unlikely to be specific to Amazon. Among tech giants, Amazon is probably least active in acquiring and funding startups. Other tech giants like Google and Facebook are more aggressive in buying and financing startups. Even for some relatively smaller tech firms like Twitter, they are also very active acquirers and strategic investors. Therefore, since the mechanisms through which this funding/acquisition channel affects entrepreneurs are unlikely to be unique to Amazon, we should expect a similar effect from other large firms that are active acquirers and strategic investors.

Over the last three decades, we saw fewer startups but more corporate giants. Entrepreneurs and startups are the engines of economic growth and innovation. Furthermore, there seems to be a growing concern about the impacts of large companies on our society. By presenting a positive funding/acquisition channel, this paper provides us a complete picture of the relation between large and small firms, which may help the public, as well as the policymakers, assess the overall impacts of the corporate giants on our society.

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Figure 1: Percentage of Funding Rounds Involving Corporate Investors

This figure shows the percentage of funding rounds from 2010 - 2018 that involve corporate investors. Corporate investors also include corporate venture capitals. All the data are from CrunchBase. Seed indicates seed round financing, Series A indicates series-A round financing, All indicates any round (early or late). The financing round information is provided by CrunchBase.

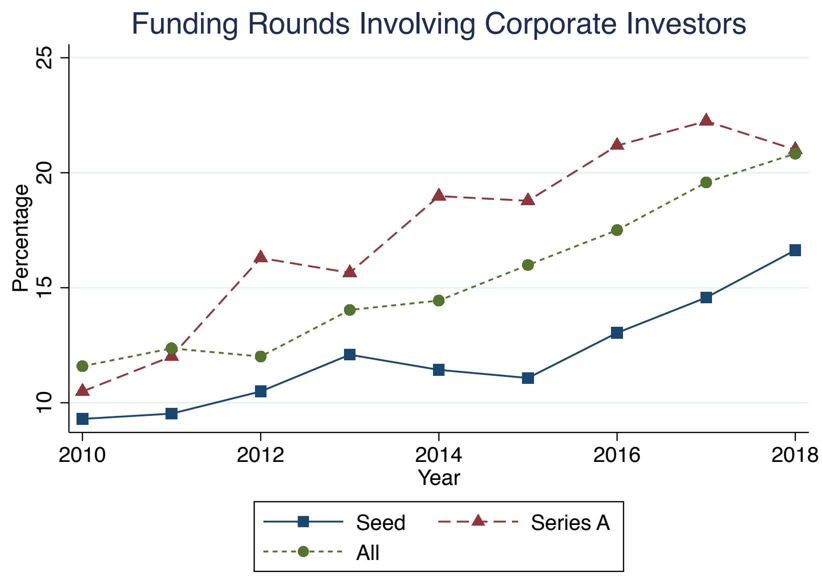


Figure 2: Startup Acquisitions vs. IPO

This figure shows the number of companies going public from 2010 to 2017 and the number of startups that were acquired with age less than or equal to 5 years. The startup acquisition data are from CrunchBase and the IPO data are taken from Jay Ritter's website.

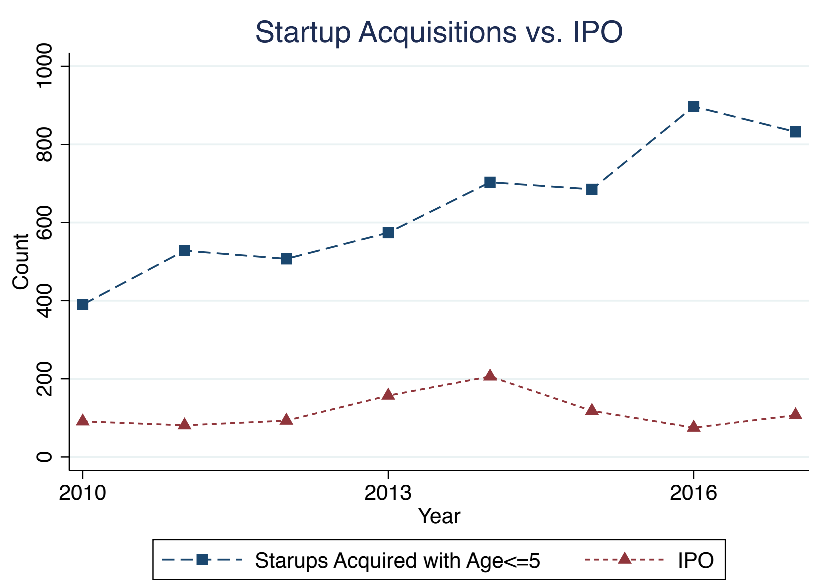


Figure 3: Amazon's 20 HQ2 Finalists

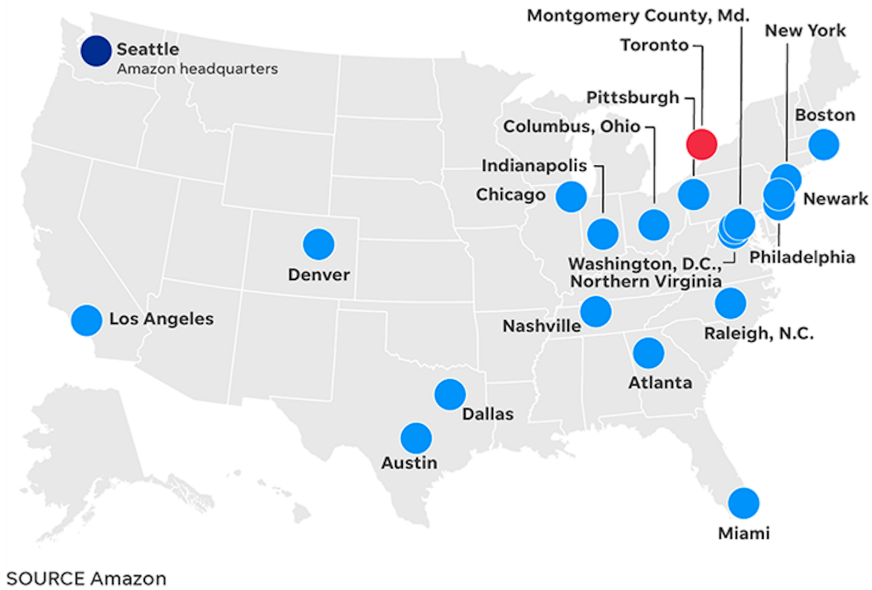


Figure 4: Geographic Distribution of Amazon's Potential Targets

This figure shows the number (natural logarithm) of Amazon's potential funding/acquisition targets established in each MSA area between 2010 and 2017. Potential acquisition/funding targets of Amazon contain the startups that are in the top 10 percentile in each year in terms of estimated probability of getting acquired/funded by Amazon. The data for this figure are from CrunchBase.

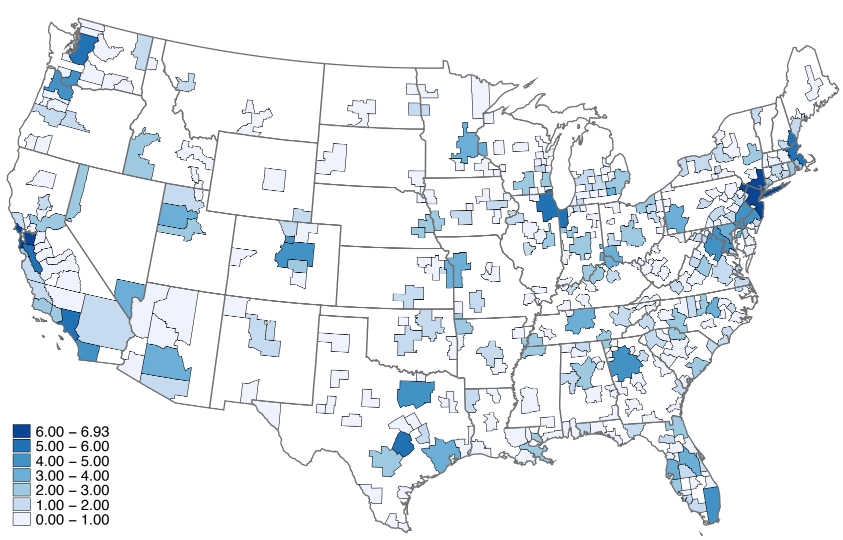


Figure 5: Percentage of New Startups Established in One of the Losing Finalist Cities

This figure shows the percentage of newly created startups for each year between January 2014 and June 2019 that were established in one of Amazon's 20 HQ2 finalist cities. The data for this figure are from CrunchBase. Likely acquisition/funding targets of Amazon contain the startups that are in the top 10 percentile in each year in terms of estimated probability of getting acquired/funded by Amazon. Unlikely acquisition/funding targets of Amazon include remaining 90% of new startups in each year.

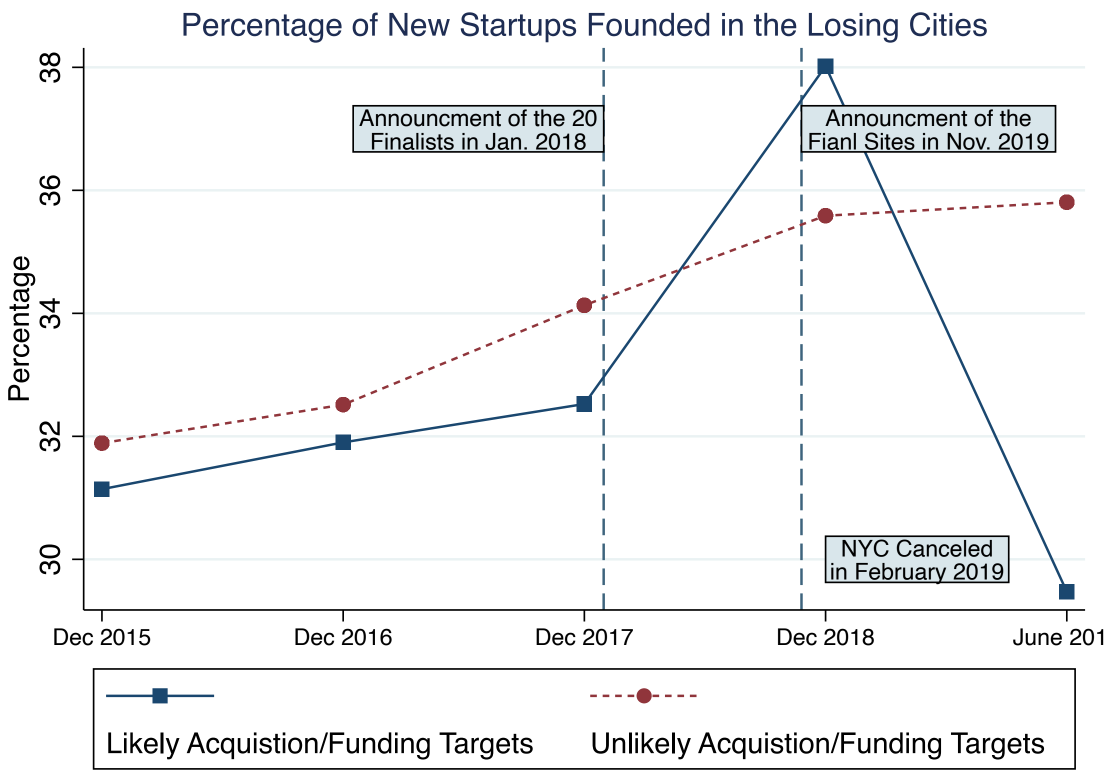


Figure 6: Percentage of New Startups Established in Northern Virginia or Washington DC

This figure shows the percentage of newly created startups for each year between January 2014 and June 2019 that were established in Northern Virginia or Washington DC. The data for this figure are from Crunch-Base. Likely acquisition/funding targets of Amazon contain the startups that are in the top 10 percentile in each year in terms of estimated probability of being acquired/funded by Amazon. Unlikely acquisition/funding targets of Amazon include remaining 90% of new startups in each year.

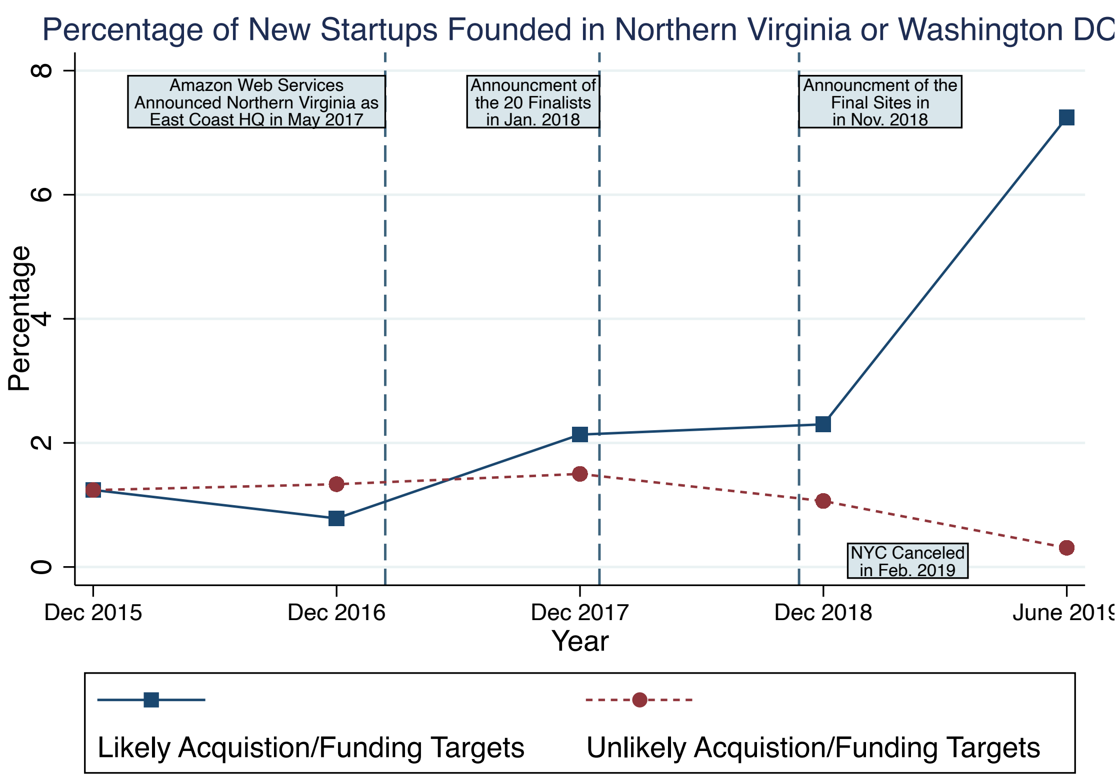


Figure 7: Dynamic Effects

This figure plots the point estimates and confidence intervals (95%) for the coefficients λ_τ from the following OLS regressions:

$$HQ2_{it}(NV\&DC_{it}) = \alpha_t + \sum_{\tau=2015}^{\tau=2019} \lambda_\tau Prob_{i\tau} \times Y_\tau + \gamma Prob_{it} + \varepsilon_{it}$$

,where $HQ2_{it}$ is a dummy variable that is equal to one if newly created startup i in year t is founded in one of the 20 Amazon HQ2 finalists, $NV\&DC_{it}$ is a dummy that is equal to one if newly created startup i in year t is founded in Northern Virginia or Washington DC, a_t is the establishment year fixed effects, $Prob_{it}$ is estimated probability of getting either invested or acquired by Amazon for startup i founded in year t, Y_τ is an indicator if it is the year τ, and ε_{it} is the error term. The sample period is from January 2014 to June 2019.

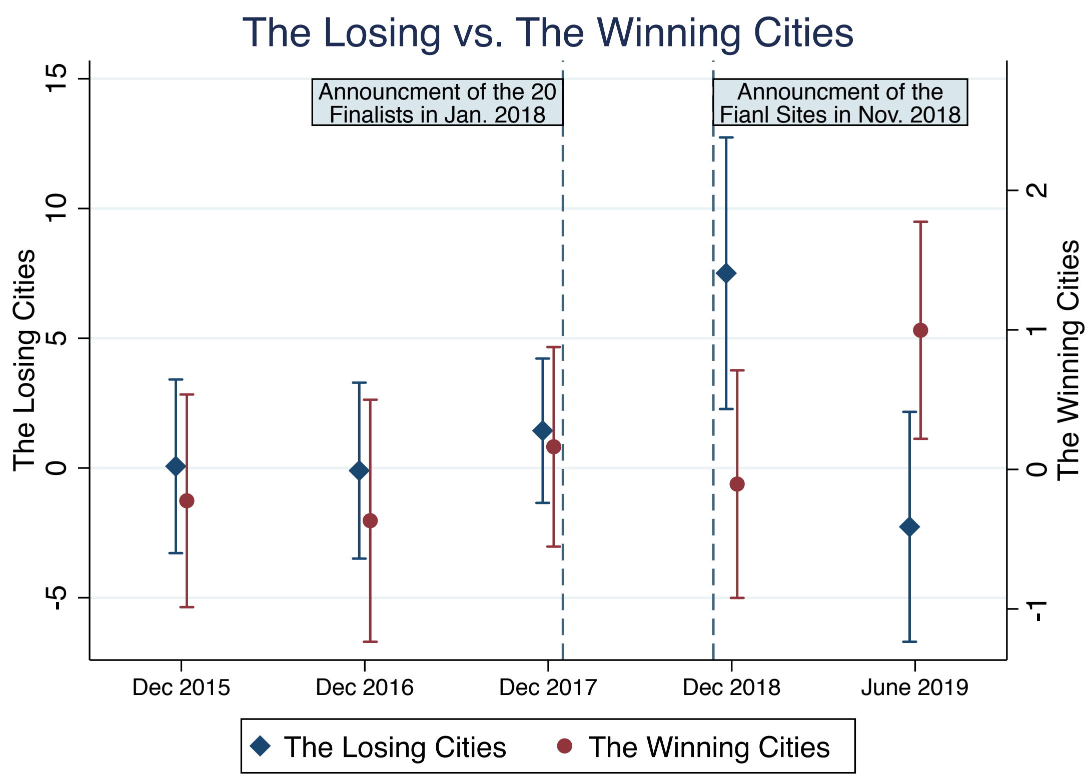


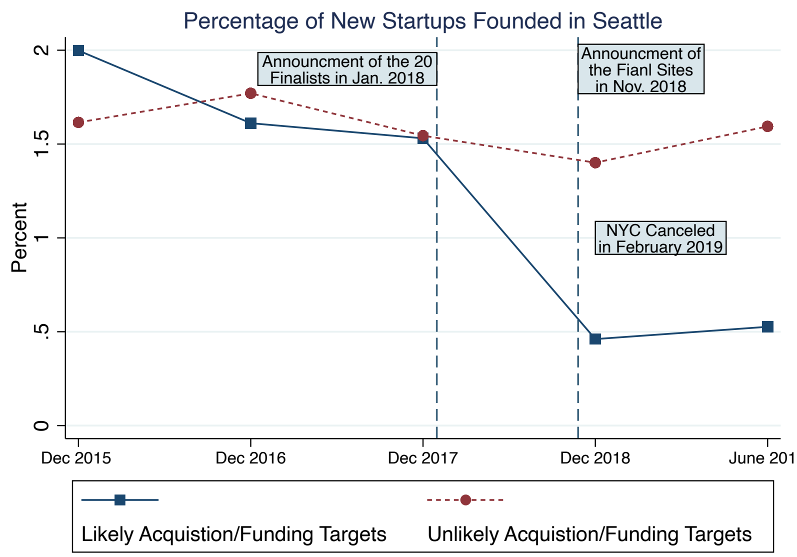
Figure 8: Seattle

Panel A shows the percentage of newly created startups for each year between January 2015 and June 2019 that were established in Seattle. The data for this figure are from CrunchBase. Likely acquisition/funding targets of Amazon contain the startups that are in the top 10 percentile in each year in terms of estimated probability of being acquired/funded by Amazon. Unlikely acquisition/funding targets of Amazon include remaining 90% of new startups in each year. Panel B plots the point estimates and confidence intervals (95%) for the coefficients λ_τ from the following OLS regressions:

$$\text{Seattle}_{it} = \alpha_t + \sum_{\tau=2016}^{\tau=2019} \lambda_\tau Prob_{i\tau} \times Y_\tau + \gamma Prob_{it} + \varepsilon_{it}$$

,where Seattle$_{it}$ is a dummy variable that is equal to one if newly created startup i in year t is founded in Seattle, a_t is the establishment year fixed effects, $Prob_{it}$ is estimated probability of getting either invested or acquired by Amazon for startup i founded in year t, Y_τ is an indicator if it is the year τ, and ε_{it} is the error term. The sample period is from January 2015 to June 2019.

Panel A: Percentage of New Startups Established in Seattle



Panel B: Dynamic Effects

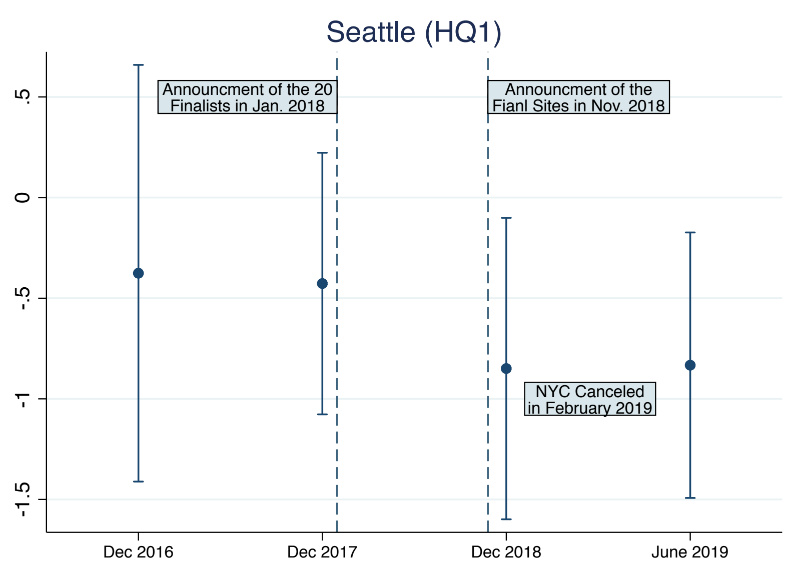


Table 1: Amazon's Revealed Preference (Keywords)

This table presents the keywords from the 69 companies (including 35 acquisition targets and 35 equity investment targets) that were founded after 2000 and were acquired or funded between 2007 and 2017 by Amazon, Amazon Web Services, a subsidiary of Amazon, and the Alexa Fund, the corporate venture capital of Amazon. The keywords are provided by CrunchBase and are used to describe companies' products or services. Each keyword in the table appears in at least two targets' descriptions because of the emphasis on the product or technology that Amazon continues to be interested in. Column (1) is equal to one if a funding target has a certain keyword, column (2) is equal to one if acquisition target has a certain keyword, column (3) indicates if a keyword is associated with Amazon's potential suppliers, column (4) indicates if a keyword is associated with Amazon's potential competitors, and column (5) shows the number of startups founded after 2000 in the CrunchBase database have a certain keyword. For more information regarding the keywords, the suppliers, and the competitors, please see Table OA1, Table OA3, and section OA.1, respectively.

Keyword	Funding Target (1)	Acquisition Target (2)	Potential Supplier (3)	Potential Competitor (4)	Number of Startups (5)
3d technology	0	1	0	0	523
advertising	1	0	0	1	10,452
apps	1	1	1	1	9,065
artificial intelligence	1	1	1	0	5,192
big data	1	0	1	0	2,828
cloud computing	0	1	0	0	1,978
cyber security	1	1	0	0	1,543
developer apis	1	1	0	0	478
developer tools	1	1	0	0	1,005
digital media	1	0	0	1	2315
e-commerce	1	1	0	1	11,283
e-learning	0	1	0	0	767
enterprise software	1	1	1	0	6,137
fashion	0	1	0	1	3,097
machine learning	1	1	1	0	2,530
natural language processing	1	1	1	0	335
robotics	1	1	1	0	1,598
saas	1	0	0	0	6,005
smart home	1	1	1	1	329
social media	1	1	1	1	7,308
video games	0	1	0	1	955
video streaming	0	1	1	1	790
Total	16	18	10	9	55,923 (unique)

Table 2: Sample Construction

This table shows the number of new startups founded for each year in CrunchBase database. The sample period is from January 2000 to June 2019. The keyword startup refers to the startups that have at least one keyword from Table 1. Because of the data entry delay in CrunchBase, the number of new startup founded in 2016, 2017, 2018, and 2019 is substantially smaller than previous years.

Founded Year	Full Sample	Keyword Startups	Percentage of Keyword Startups
2000	4,867	1,299	27
2001	4,466	1,156	26
2002	4,169	1,079	26
2003	4,372	1,157	26
2004	4,594	1,232	27
2005	5,096	1,459	29
2006	5,758	1,738	30
2007	6,768	2,195	32
2008	7,368	2,612	35
2009	8,936	3,342	37
2010	10,133	3,942	39
2011	10,998	4,561	41
2012	12,608	5,380	43
2013	13,039	5,360	41
2014	13,025	5,369	41
2015	11,540	4,760	41
2016	8,952	3,756	42
2017	7,517	3,129	42
2018	4,146	1,680	41
2019	1,821	717	39
Total	150,173	55,923	

Table 3: Summary Statistics

This table shows the summary statistics. The sample period is from January 2015 to June 2019. The sample in this table is used for regression analyses. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. Internet is a dummy variable that is equal to one if a startup has a keyword "internet" in its business description provided by CrunchBase. Software is a dummy variable that is equal to one if a startup has a keyword "software" in its business description provided by CrunchBase. Keywords is a dummy variable that is equal to one if a startup has at least one keyword from Table 1. Supplier is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's suppliers indicated in Table 1. Competitor is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's competitors indicated in Table 1. HQ2 is a dummy that is equal to one if a newly created startup is established in one of the 20 HQ2 finalist cities. NV&DC is a dummy that is equal to one if a startup is founded in either Northern Virginia or Washington DC.

	N	Mean	Median	S.D.	Min	Max
Prob(%)	33976	0.053	0.03	0.21	0.01	21.59
Software	33976	0.407	0.00	0.49	0.00	1.00
Internet	33976	0.200	0.00	0.40	0.00	1.00
Keywords	33976	0.413	0.00	0.49	0.00	1.00
Supplier	33976	0.245	0.00	0.43	0.00	1.00
Competitor	33976	0.246	0.00	0.43	0.00	1.00
HQ2	33976	0.331	0.00	0.47	0.00	1.00
NV&DC	33976	0.014	0.00	0.12	0.00	1.00

Table 4: Amazon's Local Bias

This table shows Amazon's local bias in terms of funding and acquiring startups. The sample includes startups that were founded between 2000 and 2017. The dependent variable, Funded by Amazon, is a dummy that is equal to one if a startup is funded by Amazon between 2007 and 2017. The dependent variable, Acquired by Amazon, is a dummy that is equal to one if a startup is acquired by Amazon between 2007 and 2017. *Prob* measures the probability of a startup getting funded or acquired by Amazon. Seattle is a dummy that is equal to one if a startups is founded in Seattle. Silicon Valley is a dummy that is equal to one if a startups is founded in San Jose, Palo Alto, Menlo Park, Redwood, Cupertino, Santa Clara, Mountain View, and Sunnyvale. For all specifications, z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	Funded by Amazon		Acquired by Amazon		Acquired/Funded by Amazon	
	Logit (1)	Logit (2)	Logit (3)	Logit (4)	Logit (5)	Logit (6)
Seattle	2.357***	2.312***	1.774***	1.710***	1.821***	1.756***
	(5.688)	(5.456)	(2.875)	(2.780)	(4.693)	(4.694)
Silicon Valley	0.299	0.312	0.921*	0.973**	0.643	0.678
	(0.397)	(0.410)	(1.863)	(1.993)	(1.438)	(1.544)
Seattle×Prob					197.678***	221.441***
					(7.207)	(9.787)
Silicon Valley×Prob					34.453***	35.956***
					(2.652)	(3.237)
Prob					22.173***	24.310***
					(6.586)	(6.035)
Founded Year FE	No	Yes	No	Yes	No	Yes
N	144162	115947	144162	106861	144162	135544

Table 5: Main Results - The 20 Finalist Cities

This table shows the results of difference-in-differences regressions for the newly created startups for each year between January 2015 and June 2019. The dependent variable HQ2 is a dummy that is equal to one if a newly created startup is established in one of the 20 HQ2 finalist cities. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. Keywords is a dummy variable that is equal to one if a startup has at least one keyword from Table 1. Internet is a dummy variable that is equal to one if a startup has a keyword "internet" in its business description provided by CrunchBase. Software is a dummy variable that is equal to one if a startup has a keyword "software" in its business description provided by CrunchBase. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	HQ2					
	Logit			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
2018×Prob	38.309***	48.684***	38.549***	6.768***	7.206**	6.808***
	(2.886)	(3.437)	(2.897)	(2.761)	(2.649)	(2.840)
2019×Prob	-28.031	-13.620	-19.362	-3.005	-1.870	-2.284
	(-0.706)	(-0.335)	(-0.601)	(-1.492)	(-0.855)	(-1.175)
Prob	-21.774***	-34.792***	-21.846***	-2.920***	-3.904***	-2.927***
	(-3.737)	(-4.301)	(-3.415)	(-3.894)	(-3.394)	(-3.644)
2018×Keywords		-0.053			-0.009	
		(-0.744)			(-0.547)	
2019×Keywords		-0.137*			-0.030*	
		(-1.831)			(-1.877)	
Keywords		0.122***			0.025***	
		(5.053)			(4.735)	
2018×Internet			-0.061			-0.013
			(-0.821)			(-0.778)
2019×Internet			-0.035			-0.008
			(-0.416)			(-0.396)
2018×Software			0.012			0.003
			(0.208)			(0.243)
2019×Software			-0.158***			-0.036***
			(-3.154)			(-3.278)
Software			-0.020			-0.005
			(-0.870)			(-1.016)
Internet			0.065**			0.014**
			(2.111)			(2.082)
Founded Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	33,976	33,976	33,976	33,976	33,976	33,976

Table 6: Main Results - Northern Virginia and Washington DC

This table shows the results of difference-in-differences regressions for the newly created startups for each year between January 2015 and June 2019. The dependent variable NV&DC is a dummy that is equal to one if a startup is founded in either Northern Virginia or Washington DC. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. Keywords is a dummy variable that is equal to one if a startup has at least one keyword from Table 1. Internet is a dummy variable that is equal to one if a startup has a keyword "internet" in its business description provided by CrunchBase. Software is a dummy variable that is equal to one if a startup has a keyword "software" in its business description provided by CrunchBase. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	Northern Virginia & Washington DC					
	Logit			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
2018×Prob	-23.564	50.556	-22.972	-0.052	0.129	-0.027
	(-0.142)	(0.647)	(-0.159)	(-0.211)	(0.558)	(-0.113)
2019×Prob	86.996**	105.354*	63.024*	1.051***	1.330***	1.020***
	(2.069)	(1.935)	(1.659)	(4.948)	(7.108)	(4.312)
Prob	-62.121	-69.704	-36.578	-0.247**	-0.252*	-0.162
	(-1.483)	(-1.282)	(-0.976)	(-2.132)	(-1.976)	(-1.470)
2018×Keywords		-0.387			-0.005	
		(-1.320)			(-1.296)	
2019×Keywords		-0.752**			-0.010**	
		(-2.029)			(-2.159)	
Keywords		0.035			0.000	
		(0.298)			(0.087)	
2018×Internet			-0.389			-0.005*
			(-1.259)			(-1.852)
2019×Internet			0.572			0.008
			(1.610)			(1.327)
2018×Software			0.111			0.001
			(0.389)			(0.314)
2019×Software			-0.299			-0.005
			(-0.693)			(-0.739)
Software			-0.152			-0.002
			(-1.250)			(-1.382)
Internet			-0.252*			-0.003*
			(-1.874)			(-1.985)
Founded Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	33,976	33,976	33,976	33,976	33,976	33,976

Table 7: Local Compeition for Getting Acquired or Funded by Amazon

This table presents evidence that there is local competition for startups to be acquired or funded by Amazon. Each observation is a MSA area and I exclude MSA areas that never had a single potential target of Amazon (top 10% in terms of the estimated probability) established there. The dependent variable, Number of Targets in 2018, is the number of potential targets of Amazon (top 10% in terms of the estimated probability) established in a given MSA area in 2018. The variable, Probability to be Chosen by by Amazon, is the probability provided by Paddy Power (please see Table 8 for more details). It is equal to **zero for the non-finalist cities** and equal to **one for Seattle**. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	Number of Targets in 2018			
	Including Seattle		Excluding Seattle	
	(1)	(2)	(3)	(4)
Probability to be Chosen by Amazon	0.059	0.053	0.230**	0.211*
	(1.526)	(1.418)	(2.080)	(1.865)
Number of $\text{Targets}_{[2010,2017]}$	-0.067*		-0.065*	
	(-1.742)		(-1.679)	
Number of $\text{Targets}_{[2014,2017]}$		-0.081***		-0.078***
		(-3.860)		(-3.660)
N	142	142	141	141

Table 8: Probabilities to be Chosen by Amazon

These are the odds ratios provided by Paddy Power, a betting website, that indicate the probability that each finalist city would be chosen by Amazon as its HQ2 site. These odd ratios are published on Jan 19, 2018, the next day after Amazon announced the 20 finalist cities for its HQ2.

Bets will be settled on the City Amazon announce in 2018 will be the location for their second headquarters

Boston	3/1	New York	14/1	Nashville	20/1
Austin	7/2	Toronto	14/1	Indianapolis	20/1
Atlanta	7/2	Chicago	16/1	Raleigh	20/1
Montgomery County	8/1	Denver	16/1	Dallas	20/1
Pittsburgh	8/1	Newark	16/1	Northern Virginia	20/1
Washington D.C.	10/1	Columbus	20/1	Miami	20/1
Philadelphia	14/1	Los Angeles	20/1		

Table 9: Suppliers

This table shows the results of difference-in-differences regressions for the newly created startups for each year between January 2014 and June 2019. The dependent variable HQ2 is a dummy that is equal to one if a newly created startup is established in one of the 20 HQ2 finalist cities. The dependent variable NV&DC is a dummy that is equal to one if a startup is founded in either Northern Virginia or Washington DC. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. Supplier is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's suppliers indicated in Table 1. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	HQ2		Northern Virginia & DC	
	Logit	OLS	Logit	OLS
	(1)	(2)	(3)	(4)
2018×Prob	48.818***	7.976***	-18.413	-0.047
	(3.355)	(3.292)	(-0.098)	(-0.148)
2019×Prob	-19.079	-2.199	73.866*	1.145***
	(-0.506)	(-1.175)	(1.874)	(3.951)
Prob	-29.028***	-3.505***	-42.579	-0.182*
	(-4.248)	(-3.685)	(-1.103)	(-1.785)
2018×Supplier	-0.161**	-0.034**	0.000	-0.000
	(-2.136)	(-2.004)	(0.001)	(-0.062)
2019×Supplier	-0.099	-0.023	-0.246	-0.004
	(-0.533)	(-0.559)	(-0.513)	(-0.570)
Supplier	0.080***	0.016***	-0.120	-0.002
	(3.485)	(3.135)	(-0.941)	(-1.171)
Founded Year FE	Yes	Yes	Yes	Yes
N	33,976	33,976	33,976	33,976

Table 10: Subsample Tests - Competitors

This table presents subsample tests to compare the competitor status of the likely targets of Amazon between those established in one of the 20 finalist cities and those established in other Northern American cities. The sample contains the startups that were established between 2015 and 2018. The dependent variable, Competitor, is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's competitors indicated in Table 1. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. 2018 is a dummy variable and is equal to one if the year is 2018. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	Competitor			
	The 20 Finalist Cities		Other Cities	
	Logit	OLS	Logit	OLS
	(1)	(2)	(3)	(4)
2018×Prob	-77.725***	-49.167***	53.159	17.389
	(-11.220)	(-4.066)	(0.666)	(1.599)
Prob	440.419***	62.052***	247.915***	14.638***
	(63.578)	(5.778)	(5.636)	(2.767)
Founded Year FE	Yes	Yes	Yes	Yes
N	10,559	10,615	21,540	21,540

Table 11: Subsample Tests - External Financing

This table presents subsample tests to compare the funding status of the likely targets of Amazon between those established in one of the 20 finalist cities and those established in other Northern American cities. The sample contains the startups that were established between 2015 and 2018. In Panel A, the dependent variable, VC-Backed, is a dummy that is equal to one if a startup accepted equity investment from a VC firm as of June 2019. In Panel B, the dependent variable, External Financing, is a dummy that is equal to one if a startup accepted accepted external funding from any non-corporate investor (not including bank lending) as of June 2019. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. 2018 is a dummy variable and is equal to one if the year is 2018. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Panel A: VC-Backed

Dependent Variable:	VC-Backed			
	The 20 Finalist Cities		Other Cities	
	Logit (1)	OLS (2)	Logit (3)	OLS (4)
2018×Prob	-186.446***	-33.383***	-20.895	-3.619
	(-5.528)	(-6.815)	(-0.578)	(-0.674)
Prob	180.603***	32.906***	42.742*	6.445*
	(5.774)	(6.811)	(1.722)	(1.899)
Founded Year FE	Yes	Yes	Yes	Yes
N	10,615	10,615	21,540	21,540

Panel B: External Financing from Non-corporate Investors

Dependent Variable:	External Financing			
	The 20 Finalist Cities		Other Cities	
	Logit (1)	OLS (2)	Logit (3)	OLS (4)
2018×Prob	-164.255***	-32.440***	-32.320	-4.901
	(-5.313)	(-6.305)	(-0.880)	(-0.843)
Prob	166.593***	32.852***	40.848	6.369*
	(5.884)	(7.155)	(1.508)	(1.781)
Founded Year FE	Yes	Yes	Yes	Yes
N	10,615	10,615	21,540	21,540

Table 12: Local vs. Non-local Entrepreneurs

This table shows the results of difference-in-differences-in-differences (triple-diff) regression interacted with dummy variable *Local*, indicating if the founder or one of the co-founders of a startup is a local entrepreneur. The sample contains the startups that were established between 2015 and 2018. The startups founded in 2019 are excluded because many founders' information of those startups are missing. A local entrepreneur is defined as either went to a college or had a previous job in the same city as the current startup's founding location. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. 2018 is a dummy variable that is equal to one if the year is 2018. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	HQ2	
	Logit	OLS
	(1)	(2)
2018×Prob×Local	-214.295**	-12.645***
	(-2.052)	(-2.847)
2018×Prob	72.670	6.539**
	(0.666)	(2.441)
2018×Local	0.281	0.046
	(1.531)	(0.909)
Prob×Local	-28.287*	-4.488
	(-1.685)	(-1.518)
Local	0.146***	0.031***
	(5.545)	(5.608)
Prob	-0.718	-0.152
	(-0.057)	(-0.057)
Founded Year FE	Yes	Yes
N	24,980	24,980

Online Appendix

OA.1 Amazon's Competitors

The following information is extracted from Amazon's 10k, in which Amazon specifies its competitors.

1. Physical, e-commerce, and omnichannel retailers, publishers, vendors, distributors, manufacturers, and producers of the products we offer and sell to consumers and businesses.
2. Publishers, producers, and distributors of physical, digital, and interactive media of all types and all distribution channels.
3. Web search engines, comparison shopping websites, social networks, web portals, and other online and app-based means of discovering, using, or acquiring goods and services, either directly or in collaboration with other retailers.
4. Companies that provide e-commerce services, including website development, advertising, fulfillment, customer service, and payment processing.
5. Companies that provide fulfillment and logistics services for themselves or for third parties, whether online or offline.
6. Companies that provide information technology services or products, including on premises or cloud-based infrastructure and other services.

Table OA1: Keyword Details

This table presents keywords that appear at least twice in the sample deals in Table OA3. The reason of this requirement is to select technologies or products that Amazon continues to be interested in. The keywords are provided by CrunchBase describing company's products or services. Panel A contains all the keywords used for estimating the probability of getting acquired or funded by Amazon. Panel B shows the keywords that are removed because they are too general. Each keyword in Panel B has a more specific corresponding keyword in Panel A. Mobile corresponds to apps; consumer electronics corresponds to smart home; video corresponds to either video games or video streaming; security corresponds to cyber security; content corresponds to digital media, wireless corresponds to apps; music corresponds to digital media, marketing corresponds to advertising; android corresponds to apps; marketplace corresponds to e-commerce; audio corresponds to digital media; shopping corresponds to e-commerce; analytics corresponds to big data or artificial intelligence; education corresponds to e-learning; ios corresponds to apps; media and entertainment corresponds to digital media or video steaming.

Panel A	
Keywords	
3d technology	saas
advertising	smart home
apps	social media
artificial intelligence	video games
big data	video streaming
cloud computing	robotics
cyber security	enterprise software
developer apis	fashion
developer tools	natural language processing
e-commerce	machine learning
digital media	e-learning

Panel B	
Keywords	
software	information technology
mobile	marketing
consumer electronics	android
hardware	marketplace
video	audio
internet	beauty
internet of things	shopping
security	analytics
electronics	education
content	ios
wireless	media and entertainment
music	

Table OA2: Probability Estimation

This tables presents Logit model estimating the probability of being funded or acquired by Amazon based on the keywords in Table 1. The sample includes all the Northern American companies founded between 2000 and 2017 in CrunchBase database, and excludes companies closed or acquired before 2007, given that the deal sample is constructed after 2007. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Acquired/Funded by Amazon
3d technology	2.018***
	(0.730)
advertising	-0.037
	(0.528)
apps	0.419
	(0.417)
artificial intelligence	0.712
	(0.583)
big data	0.285
	(0.636)
cloud computing	0.939*
	(0.567)
cyber security	1.745***
	(0.527)
developer apis	1.197
	(0.793)
developer tools	1.451**
	(0.631)
digital media	1.007*
	(0.607)
e-commerce	0.272
	(0.455)
e-learning	1.932***
	(0.730)
enterprise software	0.946**
	(0.404)
fashion	1.029
	(0.629)
machine learning	0.005
	(0.720)
natural language processing	1.531*
	(0.837)
robot	1.745***
	(0.534)
saas	-0.501
	(0.625)
smart home	3.155***
	(0.542)
social media	0.450
	(0.485)
video games	1.339*
	(0.757)
video streaming	1.790***
	(0.642)
N	148827

Table OA3: Past Acquisition/Funding Deals of Amazon

The following 4 tables contain 69 companies that were founded after 2000 and were acquired or funded between 2008 and 2017 by Amazon, Amazon Web Services, a subsidiary of Amazon, and the Alexa Fund, the corporate venture capital of Amazon. The keywords are provided by CrunchBase and are used to describe companies' products or services. Column 4 of each table indicates if the target startup was a supplier of Amazon before Amazon made the acquisition or took the equity stake. The suppliers information comes from various media sources, which are shown after the last table.

Name	City	Acquired/Funded Year	Amazon's Supplier?	Keywords
Bill Me Later	lutherville timonium	Funded in 2007	No[1]	credit, e-commerce, payments
Kiva Systems	north reading	Acquired in 2012	Yes[2]	hardware, mobile, robotics, software
Woot	carrollton	Acquired in 2010	No[3]	electronics, fashion, wine and spirits
Wikia	san francisco	Funded in 2014	No[4]	creative agency, online portals, social media
Quidsi	jersey city	Acquired in 2010	No[5]	e-commerce
Animoto	new york	Funded in 2011	No[6]	music, photography, digital media, video
Elemental Technologies	portland	Acquired in 2015	Yes[7]	content delivery network, enterprise software, video, video streaming
Engine Yard	san francisco	Funded in 2009	No[8]	apps, infrastructure, paas, software, web development, web hosting
Rooftop Media	san francisco	Acquired in 2014	No[9]	audio, content, content syndication, music, news, product design, digital media
Reputation.com	redwood city	Funded in 2008	Unknown	enterprise software, internet, reputation, saas, social media
SnapTell	palo alto	Acquired in 2009	No[10]	advertising, marketing, mobile
Shelfari	seattle	Funded in 2007 & Acquired in 2008	Yes[11]	social media, social network
Clique	los angeles	Funded in 2017	Unknown	advertising, brand marketing, content, digital media, fashion, lifestyle
Lexcycle	portland	Acquired in 2009	No[12]	ios, mobile
UpNext	new york	Acquired in 2012	No[13]	3d technology, enterprise software, mobile
Double Helix Games	irvine	Acquired in 2014	No[14]	developer platform, pc games, video games
Comixology	new york	Acquired in 2015	No[15]	cloud data services, comics, digital entertainment, digital media, reading apps

Table OA3 Continued

Name	City	Acquired/Funded Year	Amazon's Supplier?	Keywords
ParAccel	campbell	Funded in 2011	No[16]	analytics, big data, information technology
Songza	long island city	Funded in 2013	No[17]	media and entertainment, music, music venues, musical instruments, digital media
Goodreads	santa monica	Acquired in 2013	Yes[18]	e-learning, social media
Yieldex	new york	Funded in 2009	No[19]	advertising, developer tools, digital media
Quorus	seattle	Acquired in 2011	No[20]	software
Videolicious	new york	Funded in 2013	Yes[21]	software, video, video streaming
Acquia	boston	Funded in 2014	No[22]	computer, content, enterprise software
TeachStreet	seattle	Acquired in 2012	No[23]	charter schools, education
Sonian	waltham	Funded in 2010	No[24]	cloud computing, e-commerce, email, enterprise software, saas
LivingSocial	washington	Funded in 2013	No[25]	advertising, e-commerce, marketing, marketplace, online auctions
Twitch	san francisco	Acquired in 2014	No[26]	social media, video, video games, video streaming
Twilio	san francisco	Funded in 2015	No[27]	enterprise software, internet, sms, voip
Foodista	seattle	Funded in 2009	No[28]	cooking, developer tools, hospitality
Adero	santa barbara	Funded in 2017	Yes[29]	smart home, consumer electronics, hardware, internet of things, mobile, software, wireless
Immedia	andover	Acquired in 2017	No[30]	consumer electronics, electronics, information technology, semiconductor
Touchco	new york	Acquired in 2010	No[31]	hardware, software
Dragon Innovation	cambridge	Funded in 2015	No[32]	hardware, software

Table OA3 Continued

Name	City	Acquired/Funded Year	Amazon's Supplier?	Keywords
Graphiq	santa barbara	Acquired in 2017	Yes[33]	artificial intelligence, big data, data visualization, market research, search engine, semantic web
Safaba Translation Solutions	pittsburgh	Acquired in 2015	Unknown	software, translation service
Blink	andover	Acquired in 2017	No[34]	consumer electronics, electronics, hardware, security
TenMarks Education	burlingame	Acquired in 2013	No[35]	e-learning, edtech, education
Shoefitr	pittsburgh	Acquired in 2015	Unknown	e-commerce, fashion, personalization, software
Thinkbox Software	winnipeg	Acquired in 2017	No[36]	software
Cloud9 IDE	san francisco	Acquired in 2016	No[37]	cloud computing, enterprise software, mobile, software
Orange Chef	san francisco	Funded in 2015	Unknown	consumer electronics, hardware, manufacturing, software, apps
Ionic Security	atlanta	Funded in 2016	No[38]	cyber security, information technology, intellectual property, security
Annapurna Labs	san jose	Acquired in 2015	No[39]	cloud computing, cloud storage, data storage
2lemetry	denver	Acquired in 2015	Unknown	cloud computing, internet of things, software
Amiato	palo alto	Acquired in 2015	No[40]	analytics, real time, service industry
MOJIO	vancouver	Funded in 2016	Yes[41]	android, apps, fintech, internet, ios, mobile, robotics, software, wireless
Scout	chicago	Funded in 2015	Unknown	consumer electronics, hardware, internet of things, security, software, smart home
Ring	santa monica	Funded in 2016	No[42]	consumer electronics, security, smart home
Biba	san francisco	Acquired in 2016	No[43]	apps, messaging, mobile
Orbeus	sunnyvale	Acquired in 2015	No[44]	apps, artificial intelligence, developer apis, enterprise software, facial recognition, image recognition, machine learning

Table OA3 Continued

Name	City	Acquired/Funded Year	Amazon's Supplier?	Keywords
Petnet	los angeles	Funded in 2015	Yes[45]	hardware, pet, robotics, software
Garageio	columbus	Funded in 2015	Yes[46]	consumer electronics, internet of things, smart home
Sutro	san francisco	Funded in 2015	Yes[47]	hardware, internet of things, smart home, software, water
AppThwack	portland	Acquired in 2015	No[48]	android, cyber security, ios, mobile, saas, test and measurement
Clusterk	palo alto	Acquired in 2015	No[49]	apps, marketing, software
Toymail Co.	new york	Funded in 2015	No[50]	children, education, e-learning
Do	san francisco	Acquired in 2017	Unknown	internet, meeting software, software
Owlet Baby Care	lehi	Funded in 2016	No[51]	baby, big data, consumer electronics, hardware, medical, mobile, software
Body Labs	new york	Acquired in 2017	No[52]	3d technology, artificial intelligence, computer vision, developer apis, machine learning
KITT.AI	seattle	Funded in 2016	No[53]	developer tools, language learning, natural language processing
Luma	atlanta	Funded in 2016	No[54]	cyber security, hardware, internet, network security
Nucleus	new york	Funded in 2016	No[55]	consumer electronics, smart home
Harvest.AI	san diego	Acquired in 2017	Unknown	artificial intelligence, cloud security, cyber security, predictive analytics
DefinedCrowd	seattle	Funded in 2016	Yes[56]	artificial intelligence, data center, machine learning, natural language processing
Stanza	bellevue	Acquired in 2009	No[57]	information services
GoButler / Angel.AI	new york	Acquired in 2016	Unknown	apps, artificial intelligence, internet, machine learning, reservations
Embodied, Inc.	pasadena	Funded in 2016	Unknown	artificial intelligence, health care, robotics, wellness
Essential	palo alto	Funded in 2017	No[58]	consumer electronics, mobile devices, smart home

Footnotes for Table OA3:

1. Amazon didn't use the BillMeLater's service when it made the investment.
Source: https://techcrunch.com/2007/12/11/amazon-invests-in-bill-me-later/

2. Kiva Systems provided software to Quidsi, which is owned by Amazon.
Source: https://xconomy.com/seattle/2012/03/19/amazon-kiva-system/

3. "Amazon (AMZN) has agreed to buy Woot, the clearance site that sells one item per day. But Amazon already has a similar last-chance feature on its own site, and it nearly always stocks the same items that Woot"
Source: https://www.cbsnews.com/news/why-is-amazon-buying-woot-the-answer-may-surprise-you/

4. "Wikia's business is built around advertising and syndication partnerships with lots of premium content publishers like Warner Bros., Carbine Studios, IGN, IDG, Roddenberry Entertainment, and Sony."
Source: https://techcrunch.com/2014/08/27/user-generated-content-portal-wikia-raises-another-15m-to-crack-into-asia/

5. Source: https://www.businesswire.com/news/home/20101108005786/en/Amazon.com-Acquire-Diapers.com-Soap.com

6. Animoto is the customer of Amazon Web Services.
Source: https://www.reuters.com/article/us-ml-amazon-cloud/amazon-finds-start-up-investments-in-the-cloud-idUSTRE7A879820111109

7. "Jeff Barr, chief evangelist for Amazon's cloud, wrote in the AWS blog that the two companies have been working together on shared sports and entertainment industry accounts for four years."
Source: https://www.crn.com/news/cloud/300078000/amazon-acquires-elemental-technologies-to-boost-aws-video-streaming-chops.htm

8. "Despite Amazon's investment, Engine Yard does not use the online retailer's Web services offering at this time. It plans to in the future, however."
Source: https://www.cnet.com/news/amazon-invests-in-engine-yards-cloud-computing/

9. "The company's partners include Apple, Yahoo, SiriusXM, Pandora, and Spotify."
Source: https://thelaughbutton.com/news/amazon-buys-comedy-service-rooftop-media/

10. "Amazon.com (AMZN - Get Report) purchased a visual product-search company that makes a popular software application for Apple's (AAPL) iPhone."
Source: https://www.thestreet.com/story/10519227/1/amazon-buys-snaptell-maker-of-iphone-app.html

11. "Users can share their library through the Shelfari website or via a widget, and make money by linking to the books for sale at Amazon."
Source: https://techcrunch.com/2007/02/25/amazon-invests-in-shelfari/

12. "Seeking to strengthen its presence on the iPhone and iPod Touch, Amazon has acquired Lexcycle, the company behind Stanza, a popular free e-book application for the iPhone"
Source: https://dealbook.nytimes.com/2009/04/27/amazon-buys-lexcycle-maker-of-e-book-application/

13. "Amazon's UpNext acquisition is curious considering that the Kindle Fire doesn't have GPS capabilities."
Source: https://www.wired.com/2012/07/amazon-acquires-3d-mapping-company/

14. "The Double Helix deal may fuel to the recent rumors that Amazon is preparing to release its own gaming console in the coming months."
Source: https://techcrunch.com/2014/02/05/amazon-acquires-video-gaming-studio-double-helix-games/

15. Amazon's Jet City put its offerings in direct competition with ComiXology.
Source: https://www.fool.com/investing/general/2014/04/23/why-amazon-acquired-comixology.aspx

16. Amazon uses ParAccel's product one year after the investment.
Source: https://techcrunch.com/2012/11/28/amazon-web-services-announces-redshift-new-data-warehouse-service/

17. "It's unclear -- even when I asked Songza -- exactly what Amazon's role is with the company. But we do know that Amazon is/has been an investor in the streaming music service."
Source: https://www.thestreet.com/story/12464923/1/amazon-music-could-be-songza.html

18. Source: https://www.publishersweekly.com/pw/by-topic/digital/retailing/article/56575-amazon-buys-goodreads.html

19. Yieldex used to be a customer of AWS but stopped using it after received funding from Amazon.
Source: https://www.reuters.com/article/amazon-cloud-idUSN1E7A727Q20111109

20. Quorus's product is used by Zappos, owned by Amazon.
Source: https://www.geekwire.com/2011/exclusive-amazoncom-quietly-acquires-social-shopping-whizzes-quorus/

21. The Washington Post uses Videolicious's apps.
Source: https://techcrunch.com/2013/08/09/videolicious-2-25m/

22. Acquia is a customer of AWS.
Source: https://www.cmswire.com/cms/web-cms/whose-idea-was-this-amazons-investment-in-acquia-026198.php

23. A talent acquisition and TeachStreet will be shut down after the acquisition.
Source: https://www.geekwire.com/2012/exclusive-amazoncom-buys-teachstreet/

24. Sonian is a customer of AWS.
Source: https://techcrunch.com/2012/05/31/more-cloud-investment-sonian-picks-up-13-6m-for-cloud-archiving-and-search/

25. "It's unclear as to how LivingSocial may factor into Amazon's local sales plans--it's an investment rather than an outright acquisition, after all."
Source: https://www.cnet.com/news/amazon-fuels-livingsocial-with-175-million/

26. "Amazon's Twitch buy was an investment in bolstering Amazon Web Services (AWS), the company's $7 billion-plus cloud-computing juggernaut...And with AWS facing intense competitive pressure from Microsoft Azure, a deep integration with Twitch becomes a strategic move to attract as many developers from the lucrative games market as it can."
Source: https://www.businessinsider.com/amazons-970-million-purchase-of-twitch-makes-so-much-sense-now-its-all-about-the-cloud-2016-3

27. Twilio is a customer of AWS.
Source: http://fortune.com/2015/07/29/twilio-lands-million-communicate-software/

28. Foodista is a customer of AWS.
Source: http://www.washingtonpost.com/wp-dyn/content/article/2009/04/22/AR2009042203531.html

29. Adero's product is used by Amazon Alexa.
Source: https://www.businessinsider.com/amazon-invests-in-trackrs-50-million-funding-round-2017-8

30. Immedia is a customer of Amazon.

Source: https://www.bizjournals.com/boston/news/2017/12/21/amazon-acquires-andover-basedblink-maker-of-home.html

31. "Touchco, which began as a project at the Media Research Lab at New York University, had roughly six employees and had not yet turned its technology into a commercial product."

Source: https://www.nytimes.com/2010/02/04/technology/04amazon.html

32 "The company's core service is helping hardware startups turn their ideas into working products, particularly when it comes to hiring manufacturers in China."

Source: http://www.betaboston.com/news/2015/06/25/dragon-innovation-snags-investment-from-amazons-100m-alexa-fund/

33. Graphiq's app was used by Amazon Alexa.

Source: https://readwrite.com/2017/07/23/amazon-alexa-graphiq/

34. Blink is a customer of Amazon - "As one of [Blink's] distributors, we already know customers love their home security cameras and monitoring systems. We're excited to welcome their team and invent together on behalf of customers."

Source: https://www.theverge.com/circuitbreaker/2017/12/22/16810516/amazon-blink-acquisition-smart-camera-doorbell-company

35. "Amazon likely wants to broaden the scope of its digital media business by getting into education content. It also probably wants to make its Kindle platform more attractive to public school boards, who are increasingly using annual budgets to buy tablets for its students"

Source: https://venturebeat.com/2013/10/10/heres-why-amazon-just-acquired-ed-tech-startup-tenmarks/

36. "Thinkbox's customer list includes Burrows, DK Studios, Luma Pictures, Milk VFX, and Pixomondo."

Source: https://venturebeat.com/2017/03/06/aws-acquires-media-rendering-outfit-thinkbox-software/

37. Cloud9's customers are developers.

Source: https://thenextweb.com/dd/2016/07/14/amazon-buys-cloud9-aws/

38 Two companies start a partnership after the investment.

Source: https://www.businesswire.com/news/home/20160531006618/en/Ionic-Security-Secures-45-Million-Growth

39. Annapurna Labs launched the product one year after the acquisition.

Source: https://www.theverge.com/2016/1/7/10728132/amazon-annapurna-alpine-chip

40. "The acquisition was intended for the know-how of the company's staff rather than the software and services it offered."

Source: https://www.computing.co.uk/ctg/news/2403689/amazon-buys-out-data-migration-start-up-amiato-in-hush-hush-acquisition

41. Source: https://www.moj.io/blog/series-a-funding-fueling-growth-connected-car-platform/

42. Ring sells home security camera. Source: https://www.wsj.com/articles/amazon-acquires-ring-maker-of-video-doorbells-1519768639

43. Biba is a customer of AWS.

Source: https://www.geekwire.com/2016/amazon-stealthily-bought-work-communication-company-biba-systems-last-year/

44. "Before being acquired by Amazon, Orbeus offered its image-processing solution, called Rekognition, "as-a-service" to developers."

Source: https://siliconangle.com/2016/04/06/amazon-acquired-ai-startup-orbeus-late-last-year/

45. "Petnet is building skills for Alexa enabling Echo customers to control their SmartFeeder connected appliance."

Source: https://developer.amazon.com/blogs/alexa/post/Tx1L2Q3VXTML1AI/petnet-is-the-latest-alexa-fund-recipient

46. "when Amazon opened the Echo platform to outside software and device makers, it announced Garageio as one of the first devices to work with it."

Source: https://www.bizjournals.com/columbus/blog/2015/06/inside-the-amazon-deal-with-garageio-they.html

47. Source: https://developer.amazon.com/blogs/post/Tx1NR4IYAIXWMJL/Announcing-the-Latest-Alexa-Fund-Recipient-Sutro

48. Source: https://www.geekwire.com/2015/amazons-aws-acquires-portlands-appthwack-seeking-an-easy-way-to-test-apps-in-the-cloud/

49. ClusterK's customers are developers. Source: https://www.geekwire.com/2015/amazon-buys-clusterk-a-startup-that-lets-developers-run-aws-workloads-more-cheaply/

50. Source: https://toybook.com/startup-toymail-receives-investment-from-amazon-will-integrate-alexa-voice-service-into-toys/

51. "We look forward to the future opportunities to integrate Owlet with Alexa, empowering parents with the incredible data and information provided by Owlet."

Source: https://www.mobihealthnews.com/content/owlet-raises-15m-baby-monitoring-smart-sock-plans-nih-study

52. "It's not clear exactly what Amazon intends to do with Body Labs but there are plenty of potential use-cases that mesh with and could extend its existing business interests." Source: https://techcrunch.com/2017/10/03/amazon-has-acquired-3d-body-model-startup-body-labs-for-50m-70m/

53. KITT.AI's first product was lunched after Amazon's investment.

Source: https://www.geekwire.com/2016/backed-amazon-paul-allen-kitt-ai-launches-first-hotword-detection-software-toolkit/

54. Luma was still in the beta-testing stage of its products when Amazon made the investment.

Source: https://www.recode.net/2016/4/7/11585940/luma-gets-12-5-million-amazon-accel

55. Nucleus's products were sold on Amazon.

Source: https://qz.com/981086/amazon-startup-money-for-nucleus-set-a-bad-precedent-amazon-amzn-funding/

56. "The startup is also an official partner of Amazon, which recommends the service to developers as a way to improve voice interactions with Alexa."

Source: https://www.geekwire.com/2018/crowd-service-ai-training-startup-definedcrowd-raises-cash/

57. Stanza has similar product to Amazon's kindle app for iPhone.

Source: https://www.crn.com/blogs-op-ed/the-channel-wire/217200519/what-amazon-gains-with-stanza-in-its-trickbag.htm

58. Essential didn't release any product when Amazon made the investment.

Source: https://www.engadget.com/2017/08/09/amazon-andy-rubin-essential-phone-tencent-investment/

Table OA4: Robustness Tests for the 20 Finalists Results - Different Sample Period

This table repeats the difference-in-differences regressions in Table 5 and Table 9 for different sample period. The sample includes the newly created startups between January 2017 and June 2019. The dependent variable HQ2 is a dummy that is equal to one if a newly created startup is established in one of the 20 HQ2 finalist cities. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. Internet is a dummy variable that is equal to one if a startup has a keyword "internet" in its business description provided by CrunchBase. Software is a dummy variable that is equal to one if a startup has a keyword "software" in its business description provided by CrunchBase. Supplier is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's suppliers indicated in Table 1. Competitor is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's competitors indicated in Table 1. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	HQ2					
	Logit			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
2018×Prob	41.229**	40.479**	58.595***	6.070**	6.044**	6.934**
	(2.188)	(2.249)	(2.667)	(2.472)	(2.543)	(2.726)
2019×Prob	-25.112	-17.433	-10.813	-3.703*	-3.048	-3.227*
	(-0.596)	(-0.504)	(-0.251)	(-1.841)	(-1.595)	(-1.697)
Prob	-24.694*	-23.776*	-40.501**	-2.222***	-2.163***	-2.826***
	(-1.700)	(-1.743)	(-2.300)	(-3.122)	(-3.136)	(-2.781)
2018×Internet		0.005			0.002	
		(0.044)			(0.066)	
2019×Internet		0.031			0.007	
		(0.274)			(0.287)	
2018×Software		0.005			0.002	
		(0.071)			(0.135)	
2019×Software		-0.165***			-0.037***	
		(-2.745)			(-2.815)	
Software		-0.013			-0.004	
		(-0.320)			(-0.445)	
Internet		-0.001			-0.001	
		(-0.007)			(-0.036)	
2018×Competitor			0.085			0.021
			(0.794)			(0.831)
2019×Competitor			-0.019			-0.004
			(-0.158)			(-0.161)
2018×Supplier			-0.236**			-0.050**
			(-2.514)			(-2.420)
2019×Supplier			-0.140			-0.031
			(-0.657)			(-0.648)
Supplier			0.067			0.011
			(1.142)			(0.922)
Competitor			0.168**			0.038**
			(2.350)			(2.348)
Founded Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13,484	13,484	13,484	13,484	13,484	13,484

Table OA5: Robustness Tests for the NVDC Results - Different Sample Period

This table repeats the difference-in-differences regressions in Table 6 and Table 9 for different sample period. The sample includes the newly created startups between January 2017 and June 2019. The dependent variable NV&DC is a dummy that is equal to one if a startup is founded in either Northern Virginia or Washington DC. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. Internet is a dummy variable that is equal to one if a startup has a keyword "internet" in its business description provided by CrunchBase. Software is a dummy variable that is equal to one if a startup has a keyword "software" in its business description provided by CrunchBase. Supplier is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's suppliers indicated in Table 1. Competitor is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's competitors indicated in Table 1. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	Northern Virginia & Washington DC					
	Logit			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
2018×Prob	-83.078	-64.295	-53.246	-0.267	-0.257	-0.158
	(-0.512)	(-0.458)	(-0.291)	(-1.133)	(-0.979)	(-0.480)
2019×Prob	27.485***	21.699**	41.736**	0.835***	0.790***	1.093***
	(2.730)	(2.208)	(2.386)	(4.156)	(3.082)	(3.469)
Prob	-2.609	4.748	-4.618	-0.031	0.068	-0.048
	(-0.277)	(0.621)	(-0.338)	(-0.342)	(0.462)	(-0.478)
2018×Internet		-0.090			-0.001	
		(-0.238)			(-0.319)	
2019×Internet		0.870**			0.012*	
		(2.082)			(1.800)	
2018×Software		0.203			0.003	
		(0.493)			(0.465)	
2019×Software		-0.208			-0.003	
		(-0.396)			(-0.422)	
Software		-0.243			-0.003	
		(-0.764)			(-0.801)	
Internet		-0.550**			-0.007**	
		(-2.153)			(-2.549)	
2018×Competitor			-0.196			-0.003
			(-0.484)			(-0.517)
2019×Competitor			-0.559			-0.007
			(-1.552)			(-1.598)
2018×Supplier			-0.126			-0.002
			(-0.309)			(-0.425)
2019×Supplier			-0.255			-0.004
			(-0.563)			(-0.627)
Supplier			0.096			0.001
			(0.421)			(0.411)
Competitor			-0.081			-0.001
			(-0.447)			(-0.453)
Founded Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	13,484	13,484	13,484	13,484	13,484	13,484

Table OA6: Robustness Tests for the 20 Finalists Results - Different Control Group

This table repeats the difference-in-differences regressions in Table 5 and Table 9 for different control group. The sample includes the newly created startups between January 2015 and June 2019 that have at least one keyword from Table 1. The dependent variable HQ2 is a dummy that is equal to one if a newly created startup is established in one of the 20 HQ2 finalist cities. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. Internet is a dummy variable that is equal to one if a startup has a keyword "internet" in its business description provided by CrunchBase. Software is a dummy variable that is equal to one if a startup has a keyword "software" in its business description provided by CrunchBase. Supplier is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's suppliers indicated in Table 1. Competitor is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's competitors indicated in Table 1. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	HQ2					
	Logit			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
2018×Prob	48.694***	48.159***	51.647***	7.204**	7.446***	7.963***
	(3.436)	(3.389)	(3.627)	(2.647)	(2.814)	(3.154)
2019×Prob	-13.610	-11.944	-13.751	-1.871	-1.425	-1.534
	(-0.335)	(-0.310)	(-0.356)	(-0.855)	(-0.731)	(-0.778)
Prob	-34.802***	-31.978***	-34.094***	-3.902***	-3.648***	-3.825***
	(-4.295)	(-4.114)	(-4.333)	(-3.384)	(-3.439)	(-3.454)
2018×Internet		-0.103			-0.024	-0.013
		(-1.403)			(-1.411)	(-0.987)
2019×Internet		-0.166			-0.037	-0.034
		(-0.943)			(-0.946)	(-0.922)
2018×Software		-0.061			-0.015	
		(-0.695)			(-0.724)	
2019×Software		-0.046			-0.011	
		(-0.328)			(-0.334)	
Software		-0.148***			-0.034***	
		(-5.451)			(-5.608)	
Internet		0.021			0.005	
		(0.531)			(0.529)	
2018×Supplier			-0.216**			-0.049*
			(-2.026)			(-1.946)
2019×Supplier			0.008			0.002
			(0.035)			(0.034)
Supplier			-0.020			-0.006
			(-0.503)			(-0.670)
Founded Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	14,042	14,042	14,042	14,042	14,042	14,042

Table OA7: Robustness Tests for the NVDC Results - Different Control Group

This table repeats the difference-in-differences regressions in Table 6 and Table 9 for different control group. The sample includes the newly created startups between January 2015 and June 2019 that have at least one keyword from Table 1. The dependent variable NV&DC is a dummy that is equal to one if a startup is founded in either Northern Virginia or Washington DC. *Prob* measures the probability of a newly established startup in each year getting funded or acquired by Amazon. Internet is a dummy variable that is equal to one if a startup has a keyword "internet" in its business description provided by CrunchBase. Software is a dummy variable that is equal to one if a startup has a keyword "software" in its business description provided by CrunchBase. Supplier is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's suppliers indicated in Table 1. Competitor is a dummy variable that is equal to one if a startup has a keyword associated with Amazon's competitors indicated in Table 1. For all specifications, t-stats (OLS) or z-stats (Logit) are reported in parentheses based on robust standard errors . *, **, or *** indicate that the coefficient is statistically significant at the 10%, 5%, or 1% level, respectively.

Dependent Variable:	Northern Virginia & Washington DC					
	Logit			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
2018×Prob	50.463	28.189	24.952	0.129	0.051	0.038
	(0.644)	(0.268)	(0.221)	(0.559)	(0.191)	(0.126)
2019×Prob	105.246**	90.895*	87.425*	1.330***	1.214***	1.231***
	(1.995)	(1.708)	(1.742)	(7.122)	(5.724)	(4.410)
Prob	-69.610	-59.329	-55.138	-0.252*	-0.208*	-0.206*
	(-1.275)	(-1.129)	(-1.112)	(-1.985)	(-1.722)	(-1.822)
2018×Internet		-0.190			-0.001	
		(-0.405)			(-0.301)	
2019×Internet		1.916**			0.020*	
		(2.497)			(1.997)	
2018×Software		1.185			0.013*	
		(1.453)			(1.899)	
2019×Software		-0.823			-0.007	
		(-0.997)			(-0.771)	
Software		-0.307**			-0.004**	
		(-2.178)			(-2.009)	
Internet		-0.242			-0.003	
		(-1.375)			(-1.381)	
2018×Supplier			0.536			0.007
			(0.836)			(0.934)
2019×Supplier			0.605			0.007
			(0.724)			(0.848)
Supplier			-0.241			-0.003
			(-1.622)			(-1.615)
Founded Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	14,042	14,042	14,042	14,042	14,042	14,042