Information Frictions in New Venture Finance: Evidence from Product Hunt Rankings

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Abstract

A recent explosion in startup activity, often linked to reduced experimentation costs, has made it challenging for venture capital (VC) firms to efficiently obtain information and perform due diligence. This paper explores frictions in the process of venture capital information acquisition using microdata from Product Hunt, an online platform covering a large number of technology startups' product launches. On a daily basis, launched products compete for ranking based on user upvotes – a crowdsourced measure of expected consumer demand. An exogenous downward shift in rankings leads to a 9.5% decline in seed and early-stage fundraising relative to the average probability within 6 months. Top-ranked products are disproportionately more affected by the shifts to rankings than lower-ranked products. I reconcile the findings with a theoretical framework of information acquisition, which predicts that startups with greater difficulty letting their information reach investors are more affected by these online product rankings. I provide empirical evidence that align with the theory, suggesting that the effects of product rankings are mainly driven by startup teams located away from top venture capital destinations, and more pronounced among teams with at least one female maker.

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1 Introduction

Venture capital facilitates cutting-edge innovation through funding startup companies with the potential to generate a lasting impact on consumer welfare. Many of today's large influential public companies, such as Apple and Amazon, were initially backed by venture capital. Venture capital investors help bring path-breaking technologies to the market and contribute to decisions of entrepreneurial firms through guidance and monitoring (Gompers and Lerner, 2004).

However, venture capitalists face complex information issues in their involvement with early-stage companies, which have become more relevant in recent years. Given the uncertainty around the quality of early-stage firms and the difficulty in tracking their progress, information acquisition is crucial to investors when it comes to evaluating their future profitability. The problem is relevant both in the venture capitalist's ex-ante decision to invest, and in its ex-post involvement with the venture after having committed to an investment (Bernstein et al., 2016). It is challenging to quantify frictions in the information acquisition process and identify consequences of such frictions, and past work in these areas primarily draws on descriptive and correlational evidence. (Gompers, 1995; Bhidé, 2000; Hellmann and Puri, 2002, 2000; Gompers et al., 2005; Lerner et al., 2018; Kerr et al., 2011; Hsu, 2004; Chemmanur et al., 2011).

This paper provides causal evidence that frictions in venture capitalists' information acquisition process affect their funding decisions toward early-stage startups. By leveraging features of the information environment of early-stage investors that induce exogenous shifts to startup product visibility and status, I explore the effect of these frictions on seed and early-stage startups' fundraising outcome. While past literature on how VCs gather information focus primarily on what happens post-investment, relatively less is known about the information acquisition process pre-investment where VCs select companies to be potential recipients of funding.

I use micro data from Product Hunt – an online platform where digital entrepreneurs, technology enthusiasts, and investors interact around new products that are launched on a daily basis. The platform features a third of daily launched products on the front page, where users can view and upvote these recently launches. Cumulative user upvotes determine the relative rankings of products among all featured products launched that day.

As a centralized information exchange on the latest technology products, Product Hunt generates quick daily lists of new products and ranks them according to authentic user upvotes. The product rankings provide an additional piece of information about potential consumer demand and startup's future profitability. Both upvotes and rankings are noisily determined, and the process is prone to frictions that shifts the rankings of products in ways uncorrelated with product quality and startup characteristics.

I document correlational evidence that being prominently featured on Product Hunt is associated with substantially higher fundraising probability of seed (including convertible note) and series A rounds. Being top ranked is associated with higher funding probability within 6 months of launching a product on Product Hunt. To estimate a causal relationship between product rank and funding outcome, I use the fact that exogenous factors shift rankings of products due to external reasons unrelated to the quality of the product and characteristics of its makers. Two instrumental variables are constructed based on the same underlying idea.

First, startup firms launching products on Product Hunt cannot anticipate that a major technology company such as Apple or Facebook may release new products around the same time. These new releases are often shared to Product Hunt concurrently with an official announcement or news coverage (e.g. a CNBC article), and almost always highly upvoted and top ranked. These unexpected high-impact product posts absorb upvoter attention and push down the rankings of other products launched on the same day by startup firms. BigTech and other large companies also do not have an incentive to release products at a strategic time, catering specifically to the Product Hunt platform.

Second, a number of products each day were re-launched from past submissions, and Product Hunt staff typically decides about these rescheduled launches shortly after they were submitted for the first time. Hence the re-launched products are moved into today's ranking feed in a manner that is not confounded by today's new submissions. The re-launched products are typically exposed to organic traffic for a longer period of time compared to others, and end up with more organic upvotes and higher rankings as a result. If more products and higher-impact products from the past are re-launched today, new products that are just submitted must suffer more severe "crowding out" effects.

The number of products moved and their traction among users vary over time. A higher-impact external launch is more likely to shift down the rankings of current day products. I capture the variation in the potential impact of these external launches by predicting a measure of traction for large company products and re-launches. The predicted traction measure is calculated from training a regularized Poisson model of total upvotes by the end of the launch date on all products (both featured and non-featured) submitted in the previous year, using high-dimensional product characteristics as inputs, and fitting the trained model to the current product launches. Then I sum up the predicted traction over all external launches relevant for each startup product in the sample. The procedure results in an instrument that I call the *TractionWeightedExternalLaunches*, which can be constructed for both the BigTech and the re-launch scenarios.

Using these instrumental variable strategies, I estimate that each downward shift in rankings induced by the instruments leads to a decline in the probability of raising seed (including convertible note) and series A rounds by 0.23 percentage points within 6 months, or a 9.5% decline upon the average fundraising probability of 2.43%. The magnitude of the effect of rankings depend largely upon the product's rank position. Top-ranked products are disproportionately more affected by shifts to rankings than lower-ranked products. For launched products that are ranked median and above on the daily feed, each downward shift to the rankings induced by the external launches that consist the instruments lead to 0.37 percentage points lower funding probability, or a 11.5% decline upon the average probability of 3.2%. For launched products that are ranked below median on the daily feed, each downward shift to the rankings induced by the external launches that consist the instruments lead to 0.09 percentage points lower funding probability, or a 6.2% upon the average probability of 1.5%. These effects are quantitatively substantial, and show that noisy signals from Product Hunt, despite being uncorrelated to product quality and team characteristics, affect the VCs' decisions to fund the venture.

In addition, the product rankings particularly influence fundraising by startup teams that face greater ex-ante difficulty to reaching investors and accessing capital. I outline a theoretical framework of information acquisition to explain the intuition behind the mechanism that lead to Product Hunt rankings affecting real outcomes of startups such as fundraising. I test the predictions of the theoretical framework on differential effects by relative availability of prior information, and find empirical evidence that align with the theory. The effects of product rankings are primarily driven by startup teams that have members located outside top venture capital destinations (such as San Francisco Bay Area, New York City, London, and Boston), and larger for teams with at least one female maker. To the extent that the product rankings provide some quantifiable signal about the survival probability and growth potential of startup firms, which are otherwise difficult to observe in an highly unpredictable entrepreneurial environment, lower ex-ante certainty about a venture's quality leads to more updating in real outcomes based on these rankings through the platform. The empirical results also support the idea that an online platform such as Product Hunt helps bridge existent gaps and leveling the playing field for digital entrepreneurs looking to reach venture investors.

Informal interviews with product makers suggest at least three channels at play that connects the online product rankings to real fundraising outcomes. First, makers learn about the potential of their product ideas from these rankings, and base their strategic choices (on a spectrum all the way from continue developing the prototype further, to adjusting their product strategies, to abandoning the project altogether) on the feedback elicited from the platform. Second, rankings affect user acquisition and product sign-ups, both by changing the visibility of the product *on* the platform, and affecting the influencer word-of-mouth through early-adopters who spread information about the product *offline*. Lastly, the rankings and particularly top-ranked products are a direct signal of product demand, which can be cited in a pitch deck to prove product-market fit to potential investors. All these channels lead to downstream fundraising outcomes to change directly or indirectly, as supported by the empirical findings. It is beyond the scope of this paper to distinguish between these channels, though this provides an opportunity for future research that starts with collecting data to better measure each of the intermediate outcomes along the causal chain.

This paper contributes to a few strands of research. First, it sheds light on the information acquisition process of early-stage venture capital investors and adds to the understanding of the determinants of their investment decisions (Shepherd, 1999; Kaplan and Strömberg, 2003; Kaplan et al., 2009; Gompers et al., 2016a; Bernstein et al., 2017). An experimental or quasi-experimental setting is rare to come by in past research on this topic because it is hard to investigate the causal role of information which may correlate with other factors that are hard to separate without running an experiment. The paper presents causal evidence of the effect of information frictions on funding decisions among early-stage venture capitalists, by exploiting exogenous variations in product ranks on a large online platform widely used among technology startups and investors.

Second, this paper ties into a literature on the economic impact of online platforms. A number of papers have shown that the increasing popularity of online platforms such as Yelp (Luca, 2015, 2016), AirBnB (Proserpio and Zervas, 2017; Zervas et al., 2017) and Google News (Athey et al., 2017; Jeon and Nasr, 2016) significantly impact people's daily consumption decisions through changing the way in which information is aggregated and presented online, reducing the search cost for information and making direct comparisons among alternatives easier. However, works that document similar designs of online markets that shape financial investments have been rare. This paper describes how information aggregation on Product Hunt influences investor behavior and provides empirical evidence for the causal effect of information on this online platform on early-stage venture investments. This is particularly relevant given the recent trend among early-stage VCs to experiment with making small investments in the face of a large surge in early-stage startups seeking money (Kerr et al., 2014; Kerr and Nanda, 2015; Ewens et al., 2018).

Third, from the entrepreneurs' perspective, this paper relates to a literature on leveraging the "crowd" to improve access to finance for early-stage ventures. While past literature focuses specifically on the role of crowdfunding (Agrawal et al., 2014; Yu et al., 2017) in democratizing access to capital among underrepresented founders (Mollick, 2013; Mollick and Robb, 2016; Sorenson et al., 2016), and expanding the geographic reach of capital (Sorenson et al., 2016; Agrawal et al., 2015), they have not touched on other innovative ways in which designs of markets may utilize the "crowd" to open up funding opportunities to founders who may face greater geographical frictions from being located far away from where venture capital is concentrated. This paper puts forward a new empirical phenomenon where entrepreneurs can tap into the power of the "crowd" to help obtain finance for their startups. The paper shows that crowdsourced signals on Product Hunt particularly matters for improving access to VC among geographically distant firms and founders.

Fourth, the paper adds to a nascent literature on diversity in venture capital and innovation (Gompers et al., 2016b; Gompers and Wang, 2017; Gompers et al., 2017). Lack of diversity is evident in entrepreneurship and VC, which is attributed to homophily between founders and VC investors in demographics, educational and work experience. The opacity of early-stage VCs' decisions as well as the limited information available for evaluating pre-revenue businesses are reasons for basing deals on familiarity, connections, and quantifiable signals such as founder credentials. This paper puts forth a specific channel to bridge the funding gap, which particularly helps historically disadvantaged founders. As investors are ex-ante more uncertain about these firms, Product Hunt generates signals that help open up funding opportunities to these firms more than other firms. The findings suggest that Product Hunt potentially improves inequality in access to venture funding, by allowing relatively underrepresented firms and founders to show off their products, who may otherwise lack an opportunity to get VCs' attention due to lack of credentials such as past entrepreneurial experience.

Finally, this paper introduces a novel data source on startup products potentially useful for future research in entrepreneurship. While past research has relied primarily on traditional databases that collect information at a time lag (Baron and Hannan, 2002; Reuters, 2011), Product Hunt aggregates contemporaneous product offerings which allow researchers to study up-to-date patterns of innovative activities among technology startups. As venture capitalists and other investors observe most up-to-date information about these firms and make investment decisions based on such information, measuring products contemporaneously captures the role of the "jockey" more accurately in measuring determinants to venture capitalists' decisions.

The remainder of the paper is structured as follows. Section 2 introduces the data and provides descriptive statistics. Section 3 describes the identification approach and instrument variable strategies in detail. Section 4 presents empirical results on the causal effects of external shifts to product rankings. Section 5 discusses the information mechanisms through which the effects operate, and provide more empirical results as supporting evidence. Section 6 concludes with suggestions of potential future research directions.

2 Data

This section describes data sources and sample construction. To study the information environment around early-stage ventures' experimentation choices, I use data primarily from the online platform Product Hunt, a global community and product discovery website often used by product makers and entrepreneurs to launch their latest projects and acquire early adopters. I combine Product Hunt data with venture funding data from CrunchBase by matching the two data sources across a common identifier – website domain name shared by the launched product and the firm's CrunchBase profile. I also obtain from CrunchBase supplemental data on firm and founder characteristics. All data used in this paper are obtained by scraping public information from the research and developer APIs of the websites. Summary statistics are provided toward the end of the section.

2.1 Product Hunt

In recent years, regulations that support democratization of access to investing has altered the playing field for venture investing. The JOBS act signed in September 2013 lifted the ban on General Solicitation and opened up non-accredited investors' participation in funding entrepreneurial companies. The regulatory change preceded the rise of a number of online platforms which grew to be crucial to new venture financing, including AngelList and Product Hunt.

Product Hunt was founded in December 2013, as an online community that surfaces latest cool technology products, podcast episodes, books and games. Initiated as an email list containing the founder's personal favorites, Product Hunt was able to seed growth by attracting a number of early members who actively participate in building the community from scratch by sharing and discussing products. The company gained traction and success quickly, was awarded "Best New Startup" in 2014 by TechCrunch and secured an Andreesen Horowitz-led series A round of funding within a year.

The Product Hunt community has outgrown its original purpose which is solely for "hunters" to share their own discoveries about cool products in the market. Because of the large number of digital enthusiasts and early adopters willing to interact in the community and share opinion on new products, entrepreneurs started to perceive an opportunity in using the platform to let their own new products get "hunted" and benefit from exposure to the Product Hunt community. It has accumulated a mass of attention from new ventures seeking to launch products, and because product traction is an important signal to seed and early-stage venture investors, AngelList has seen value in the platform and acquired Product Hunt in December 2016. In 2018, Over 75% of seed-stage startups has raised funding, recruited employees or launched products using AngelList and Product Hunt(AngelList, 2018).

Because of the unique way in which Product Hunt evolved as an online platform, the set of products launched on the website are a combination of large tech company releases and entrepreneurial firm launches. As large companies are not looking to seek attention or acquire users from Product Hunt, the timing of their product releases are dictated by outside factors that are exogenous to what happens on the Product Hunt website. On the other hand, entrepreneurial companies' real outcomes may be affected by their relative performance in the Product Hunt launch, and hence much delibration and preparation goes into their product launches. These characteristics are the inspiration for the empirical strategy which aims to establish causal identification of the effect of Product Hunt information signals on startups' real outcomes including their ability to secure seed and early-stage funding from investors. The empirical strategy will be covered in detail in Section 3.

2.1.1 User Community and Makers

Product Hunt features an active user community of digital entrepreneurs, early adopters of technology products, and venture investors. From the beginning of 2015Q2 to the end of 2018Q1, over 400,000 users have been active on the platform – launching, upvoting, and commenting on products. About 55% of users have a non-empty "headline" (one-line bio) indicating their roles and interests[1]. To summarizes the major roles of users who have had at least some activity on Product Hunt, extracted from these profile headlines: about 16% of active users hold jobs in the tech industry[2]; about 14% are entrepreneurs and managerial team members of startup companies[3]; 0.7% are in finance-related roles, whose headlines suggest that they are angel investors, hold

[1] To elicit information about the users from their profile headlines, I extract phrases (1- and 2-grams) from these headlines after removing special characters and stop words.

[2] Their headlines contain keywords associated with digital, development, design, user (UX/UI, user research aquisition and engagement), product, marketing (including advertisement), mobile apps (including iOS and Android), engineering, and software.

[3] Their headlines contain one or more of the following keywords including mis-spelled versions and their variants: CEO, founder, co-founder, director, executive, owner, president, VP, CTO, COO, CMO, CFO, CIO, officer, entrepreneur, chief, head, and lead.

non-junior positions at venture capital firms, or work in financial services and related professions[4].

The Product Hunt user community has grown since inception, which is powered primarily by three types of user activities: hunting, upvoting, and commenting on a product. Figure 1(A) shows the growth in the number of users who have engaged in at least one of the activities in each quarter since inception (November 2013) and until the end of the 1st quarter of 2018. For upvoting activities, I exclude *family, friend, or bot* (FFB) upvotes which are defined as upvotes by users registered no more than one day before the product's official launch date, and upvoted at least one other product within 30 days of the launch. Figure 1(B) counts the number of each type of activity on a quarterly basis for the same time period.

When users register for Product Hunt, they often use real names to join the community and interact with other users. About 83.5% of active users from the beginning of 2015Q2 to the end of 2018Q1 have a name that can be classified as a person's name, and an additional 1% of active users have names that can be identified after linking their Product Hunt profiles with their Twitter accounts[5]. Among users with names classified as belonging to a person, only 20% are female[6]. About 58% of users have linked their Twitter accounts, from which I extract additional information about their geographic locations.

A key feature of the Product Hunt community is that even though the platform is organizd around sharing products, the company puts deliberate emphasis on individuals interacting organically around these products. Product Hunt encourages people to register with real names and participate in the community by sharing and discussing products. Almost all the content is generated organically by users instead of Product Hunt staff. More specifically, users hunt products by submitting them to the platform, upvote products by clicking a button on the website, and comment on products by posting discussions to the product page. The hunter often tags members of the maker team (if they are registered users of Product Hunt), and the makers engage in discussions with the rest of the community who express interest and share feedback.

Product Hunt levels the playing field for entrepreneurs from around the world and with diverse backgrounds and credentials. Worldwide Internet connectivity enables easy access to the online platform, and lowers the barrier to participation and information crowdsourcing. Any authentic

[4]Non-junior roles at venture capital firms include partner, principal, and associate. Other financial services and related professions are identified by headlines containing keywords (including their mis-spelled versions and variants) such as angel, investor, venture, fund, capital, investment, and finance.

[5]The Python package "propablepeople" is used to parse the names to determine whether it belongs to a person, a household or an organization.

[6]I use the "genderize.io" API to infer the probability that a user is female, and label the person as female if the posterior probalility of the person being female is greater than or equal to 0.5, and the prior distribution is chosen based on the rough estimate of the proportion of users who appear to be male in such a community of digital innovators as Product Hunt.

individual is allowed to register, and those particularly enthuasiastic about digital products and technology self-select into becoming active users. Because the visibility and ranking of products are entirely driven by products' traction among Product Hunt users, they are held to somewhat more equal standards compared to offline where existing connections matter much more to entrepreneurs attempting to acquire customers or gain access to potential investors. For example, a 13-year-old Russian teenage developer and resourceful Stanford frat bros both have the chance of pulling off very successful product launches – Docket, a "Tinder for grocery" class project by the former, and Snap 2.0, an updated version of SnapChat by the latter, both scored close to 500 upvotes within 48 hours and secured No. 2 rank status of their respective launch days.

About 48% of technology product launches are initiated by makers. This means that the makers must be registered users on Product Hunt, tagged by the hunter and listed inside the product post. Among these maker launches, I extract information about the makers' geographic locations by linking to their Twitter accounts. I can identify the location of at least one member of the maker teams in about 68% of the maker-initiated technology product launches.[7] I classify the maker teams as being located in a particular continent where the largest number of team members live. For more narrowly defined regions (in particular, venture capital hub areas San Francisco, New York City, Boston, and London), I consider the maker team to be in a particular region if the majority of makers whose locations are available are in that region.

For the set of maker-initated technology product launches from the beginning of 2015Q2 to the end of 2018Q1, Table 1 shows the share of maker teams located in each continent or hub area with a large amount of venture activity. About 55% of maker teams with location information available are in North America, 31% are in Europe, 10% are in Asia (excluding China[8]), and fewer than 5% are among the rest of the world. Note that these numbers can reflect biases in the prevalence of Twitter usage (relative to Internet availability more broadly), rather than the exact geographic distribution of Product Hunt makers. Only about 21% of the maker teams are located inside a venture capital hub region (San Francisco Bay Area, New York City, Boston, and London) and a substantial amount of maker launch activity occurs outside hub regions.[9]

The gender composition of makers is skewed toward being predominantly male. Fewer than

[7] I geocode the strings provided in the location section of users' Twitter profiles by using Google Places API to determine the most plausible match of each of these strings to a geocoded location.

[8] Access to Twitter is generally blocked in China.

[9] Venture capital hub regions are defined as top destinations of funding in seed (including convertible note) and early-stage (series A) rounds, which account for more than 50% of deal value between 2015 and 2018. Data for classifying hub regions come from CrunchBase. In order of total investment amount, hub regions are San Francisco Bay Area, Beijing, Shanghai, New York City, Boston, and London. Beijing and Shanghai are not shown in Table 1 because Twitter is generally inaccessible to Product Hunt users in China.

19% of maker teams have at least 1 female member, among all product launches that tag at least 1 maker with a name recognized as a person's name. About 17% of maker teams are female-majority teams. Compared to the overall gender distribution of active users (20% female), women are even less represented among the makers. These numbers, however, are consistent with the prevailing statistics on the gender composition of technology entrepreneurship and the venture capital industry outside online platforms.

2.1.2 Product Launches and Traction

On Product Hunt, around 80 product are submitted each day competing for listing on the front page. An example of a launched product is shown in Figure 2. On October 4, 2018, Square Installments was launched to Product Hunt and secured No. 1 ranking with hundreds of upvotes garnered from the user community soon after going live. On the product page, several pieces of information are assembled including product description (in text, images, and videos), and links to homepage and social media. Users interact with the product post by clicking a red "UPVOTE" button, similarly to "liking" a post on Twitter or Facebook, and posting questions and feedback to the comment section. The top of the comment section lists the hunter and makers (if tagged) who are most often among the first to post comments and initiate discussions. Any awards such as the daily, weekly, and monthly Top Five products, as well as special prizes such as "Golden Kitty Award" are listed at the top-right corner of the product page.

Typically, the product launching process involves a hunter who assembles a list of required product information and submits a product post to the platform. The hunter may or may not identify the makers of the product, who must be registered users on Product Hunt if listed.[10] Each day Product Hunt features about a third of the submitted products on the homepage, where products get organic traffic from users in the Product Hunt community, and product views lead to upvotes and discussions. Products are typically featured shortly after they were submitted for the first time, and whether the product becomes featured depends primarily on initial traction. However, the ultimate decision is subject to Product Hunt staff discretion, and occasionally products are re-launched and featured on the next day.[11]

After being featured, a product has until the end of the launch day to attract the most

[10] Makers can hunt their own product, or invite influencers to hunt the product on behalf of the team. Hunters can simply discover the product on their own, and choose to share it to the Product Hunt community without being requested to do so by the makers.

[11] The fraction of products selected to be featured each day does not vary periodically, or systematically over time. A small number of power users have the special right to submit and feature products directly, but most hunters do not have this right, and therefore most products start equally without the gaurantee of being featured, some of which obtain enough initial traction and are bumped into the front page as a result.

attention from the user community, before tomorrow's batch of products arrive, bump down old products, and occupy users' renewed attention. Featured products are ranked among one another by cumulative upvotes obtained from the user community, relative to other products also launched that day.

Although products with the largest number of user upvotes appear to be at the top of the daily ranking feed, the rank of each product does not always follow the exact ordering of cumulative upvotes. Particular (non-organic) upvotes are excluded from the calculation, although each upvote that counts weigh equally in determining the rankings. To mimic Product Hunt's rationale for classifying certain upvotes as non-organic, I classify upvotes to be from *friend, family, or bot* (FFB) if the upvoting user registered on the same day or a day before the product launch, and had no other activity within 30 days after the launch.

Among a subset of recently featured products (specifically, in September 2018), the overall Spearman's rank-order correlation is 0.837 between products' actual rankings and non-FFB launch-day upvotes, larger than 0.823 between products' actual rankings and all launch-day upvotes.[12] Therefore, in the rest of the paper, I use the implicit product rankings constructed based on *non-FFB cumulative upvotes by the end of the launch day* to measure *product traction* on Product Hunt.

For any given product, both daily ranking and total upvotes are updated in real time, and are directly visible to anyone viewing the platform. Product rankings have several direct and indirect effects. First, they directly affect visibility of each product to the viewers. Higher-ranked products are more likely to get organic views. Product Hunt lists launched products in a condensed format, feeding quick run-downs of product rankings to viewers by day. Depending on the device (e.g. computer, or mobile app), top products load immediately but users need to scroll down and wait a few seconds before viewing the next batch of lower-ranked products.

Being top-ranked signals the product's status and traction among potential consumers. The signals are received by different types of economic agents, including product makers themselves, potential consumers, and startup investors. Conversations with makers suggest two channels leading to real effects on downstream venture outcomes such as funding. More specifically, makers primarily launch their products on Product Hunt for two reasons: (1) to get early adopters and customer sign-ups, and (2) to maintain an online presence, get publicity, and signal to external stakeholders such as investors. In addition, some makers mentioned being pleasantly surprised by the massive amount of interest users express toward their products, which suggests that launch

[12] Actual rankings are updated in real time, and are not available through the API. I scraped the rankings on the website in October 2018, for products launched in September which is the latest month before data collection.

success may influence their own perception of how promising their ideas are.

While anecdotal evidence supports the direct channel of signaling to seed and angel investors being at work (The Next Web, 2014; Fast Company, 2014; Pando Daily, 2014), alternative mechanisms where indirect effects work through intermediate steps such as increasing consumer interest and entrepreneur self-learning are also plausible. All these factors can contribute to Product Hunt having an impact on downstream outcomes which matter for venture success and fundraising.

A key design feature of Product Hunt is that products are listed by launch day. Whereas new ventures launch to gain traction for their latest products, Product Hunt users also often hunt product releases by large technology companies to share the news with the community. For example, when Amazon Go was launched on December 5, 2016, the news was shared to Product Hunt and upvoted over 6,000 times, dominating all other product launches in the daily rankings. If an entrepreneurial product were to launch on the same day, its ranking would be pushed down through no fault of its own. Even though time of the launch should not affect the quality of the product, being launched on the same day as a large technology company announces a new release leads to frictions in the perception of relative rankings by platform viewers.

As will be discussed in more detail in Section 3, the empirical strategy to identify information frictions exploits ways in which attention to a particular product is crowded out unexpectedly due to external factors unrelated to the product and its makers. These information frictions shift down the rankings of particular entrepreneurial products, in manners exogenous to product quality and maker characteristics.

2.2 Venture Funding and Auxiliary Data

This paper studies startup funding, at seed and early stages in particular. I use public data from CrunchBase to construct funding measures. CrunchBase is a crowdsourced database on venture funding announcements by entrepreneurial companies around the world, and has excellent coverage especially in recent years.

Each funding round in CrunchBase is measured with an announcement date, funding type (e.g. seed, convertible note, varies series in venture rounds, debt financing, etc), and occasionally funding amount and investor identity are also observed. However, valuation at each round is typically not available.

CrunchBase also reports company and founding team characteristics. I collect variables such as firm age, employment size, headquarter location, company category group, prior funding obtained, as well as variables related to founder demographics and experience (both as entrpreneur and as regular employee). This creates a variety of control variables for companies' ex-ante chance of survival, and appeal to potential customers and prospective investors.

To combine funding data with information on Product Hunt, I match the underlying company of each product launch to CrunchBase through linking the URL domain of the company website. If a product cannot be matched to CrunchBase, it likely has not been funded by venture investors, as the majority of startups are required to announce each round of funding, and hence their profiles would have been added to CrunchBase already[13] Startup projects hosted on third-party websites (e.g. GitHub, Shopify, Instagram) are not considered standalone companies unless they have independent websites separately. However, the sample includes products that primarily run on mobile apps – the majority of which are iPhone and Android apps, with the exception of a handful of Windows phone apps.

2.3 Sample Selection and Descriptive Statistics

The time period for the analysis sample is chosen to be from the beginning of 2015Q2 to the end of 2018Q1. This takes into account the fact that a design change of the platform in late March 2015 induced an issue in the API data with regard to product timestamps, and hence I focus on the set of clean data since 2015Q2. On the other hand, 2018Q1 is chosen to be the last quarter of the sample, given that funding outcomes are measured with a time lag in CrunchBase, so that I can track the funding status of the underlying entrepreneurial companies months after they launched products on Product Hunt. I focus exclusively on technology products, and drop other types of posts such as podcast episodes, books, games, and other non-products[14].

Because the paper focuses on new venture finance, I drop old companies founded more than 5 years prior to launching on Product Hunt. I also drop products launched by public companies (e.g. BigTech[15]) or large private companies having raised series B and later rounds (e.g. Stripe). In fact, these larger established companies are the basis of an empircal strategy later employed in the paper to identify exogenous shifts to product rankings of entreprenurial firms. Identification relies on a crucial assumption that these larger established companies release products using strategies independent of any activity that occurs on Product Hunt, and that these product releases are almost always shared to Product Hunt immediately following official announcements.

The empirical analyses focus on products sufficiently exposed to organic traffic from users.

[13] U.S.-based startups are required to file a Form D in compliance with SEC regulations, and CrunchBase regularly tracks funding announcements and updates the database. Even though there are ways to forgo filing and delay announcement, most firms eventually announce the funding. There may be a time lag between closing a deal and being recorded in CrunchBase.

[14] The exhaustive list of non-products includes news articles, blog posts, online courses, videos, infographics, calculators, events, and files.

[15] Facebook, Amazon, Google, Microsoft, and Apple

Since non-featured products rarely get organic views or clicks from Product Hunt users, I only include featured products in the sample. On a typical day, around a third of the launches are selected to be featured. The fraction of featured products varies by day, but remains fairly stable over time.

After a product is submitted and featured, it almost always has 1–2 days to get noticed and attract organic upvotes by the user community. In most cases, products are featured on the same day as they are "hunted". Occasionally, Product Hunt considers a product to be worthy of featuring but would rather re-launch it to the next day (typically around midnight). Figure 3 shows the probability of being re-launched on the next day as a function of the time of day the product is submitted.

Table 2 presents descriptive statistics of sample products and matched firms, for products ranked among the top half and among the bottom half respectively[16]. Products ranked among the top half are more likely to be matched to CrunchBase, and have better seed and early-stage funding prospects both prior to and after the launch. Higher-ranked products are on average more likely to be re-launched, more likely to tag makers, have more media content and news mentions, and are more likely to be located inside a venture capital hub region. Those who hunted products that end up among the top half in terms of rankings have 1.6 times more followers than those who hunted other products.

The sample focuses on entrepreneurial companies in seed and early stage. Table 3 provides more detailed monthly funding statistics for these companies from 2 to 12 months after they launched on Product Hunt. The firms launching products ranked in the top half are twice more likely to obtain seed or early-stage venture funding within 6 months of the launch, compared to firms launching products that end up in the bottom half of daily rankings. The overall funding probability is 2.43% within 6 months, which will serve as the baseline for benchmarking the empirical results.

Each product is tagged with a number of different topics, and I split the topics into 9 prevalence quantiles[17]. Figure 4 illustrates the aggregate relationship between topic popularity and funding outcome in each of these quantiles. Within each quantile where topic prevalence is comparable, I plot the relationship between product daily rankings and average funding probabilities. Topics with higher average rankings are associated with better seed and early-stage funding prospects within 6 months of the product launch, and this relationship appears to hold stably across all

[16] The overall median daily rank in the data is 13. The top half include products ranked 13 or higher, and the rest of the products are in the bottom half.

[17] Topics associated with fewer than 25 products in the sample are dropped. "Tech" is also dropped as a topic, because almost all products in the sample are by definition technology products.

ranges of topic prevalence.

3 Identification Approach

This section describes the identification strategy. I start with measurement of the endogenous regressor, product daily rankings, and explain ways in which this is a useful heuristic for "information" related to startups that launch products. Then I discuss sources of frictions in this "information" heuristic caused by external events unrelated to the product's quality or the startup's strategic decisions. These frictions open up the opportunity to identify a causal relationship between product rankings and downstream startup outcomes.

3.1 Product Rankings and Information Frictions

Products launched to Product Hunt are organized into daily ranking feeds, on the day of their official launch. Conditional on being selected to be in the "featured" section[18], products are ranked against all other products also launched that day, by an algorithm that primarily relies on cumulative upvotes but also takes into account factors such as time since posting and non-organic upvoting.

Figure 5 shows the top products on the launch ranking feed of June 6, 2019 in three different settings. Subfigure 5A shows the rankings on a desktop computer[19], 5B shows the rankings on an iPhone device – both for the current day's top launches which are the primary destination of any organic traffic on the platform. Subfigure 5C shows historical archives of launched products, organized also by day, and the products ranked by organic upvotes[20].

These product rankings provide information to outsiders who may not normally be a Product Hunt user regularly, but can access the website as long as they are on the Internet. This allows the information to reach a large audience in diverse geographic locations and varying business connections. I conducted interviews and surveys with a handful of makers who have launched products on Product Hunt that become featured, and ask them about the ex-ante reason for launching on Product Hunt, as well as their ex-post reflection about what they gained from the launch. These anecdotal episodes suggest three primary mechanism through which the launch

[18]On average, a third of daily submissions become "featured" eventually, either on the same day of submission or on the next day, with rare exceptions.

[19]Note that the fourth place is always a paying product that was been launched in the past, and the spot is reserved for a different old product every day.

[20]In the ranking of archived products, the 5th place is a different product than in the daily feed that is active on the homepage (under "today"). The two rankings are highly correlated but not always identical, because Product Hunt may use a slightly different algorithm between the current feed and historical ones. To identify the causal effect of rankings, though, the strategy is to exploit external shifts to the rankings uncorrelated with these noisily measured rankings.

outcome may have real effects.

First, a successful or unsuccessful launch affects the entrepreneur or product maker's own assessment of the potential of the project or idea. Makers who launched products that end up being among the top-ranked of the day are often pleasantly surprised by the outcome, compared to those who are less enthusiastic when their launches are featured but not among the very top ranked. Especially for makers who did not have prior entrepreneurial experience, other data on the external demand for their current product or assessment of the potential of their idea, the signal from Product Hunt rankings can affect their belief about how promising are their projects, and consequently, whether they are going to scale the project or develop them further into full-fledged businesses.

Second, the launch rankings directly affect the product's visibility on the website, and hence exposure to early adopters and influencers who are users of Product Hunt. These Product Hunt users may talk to friends and colleagues offline and generate even more demand through word-of-mouth, since they are the enthusiasts and influencers who like products. In this sense, the product rankings directly affect consumer acquisition, and hence product sales and other downstream startup outcomes.

Third, the launch rankings can be a direct signal that the founder team uses to attract investors. Digital startups need an online profile and collection of all the crucial information about their key products *in one place*, and Product Hunt is a way to aggregate pieces of product information and streamline the process of showcasing the strengths of the products to external stakeholders. When the startups pitch investors, they can include a direct link to their launches on Product Hunt.

The rankings are determined by an internal algorithm, in which the primary inputs are the upvotes on the products. These rankings are updated in real time, according to the cumulative upvotes on the product. The data that is currently available does not allow me to know the *exact* ranking of all featured products *at any given point in time*. I describe an approach to measure rankings approximately, and provide evidence that it captures the actual rankings to a reasonable degree of accuracy.

From a first glance at the product feed, rankings appear highly correlated with cumulative upvotes with occasional exceptions. These exceptions are largely explained by the presence of non-organic upvotes[21]. The exact definition of an "organic" upvote is only known to Product Hunt

[21] The Product Hunt algorithm flags some upvotes as inauthentic, and either does not count them in the ranking algorithm, or penalizes them by having these upvotes negatively impact a product's ranking. Factors indicating spam upvotes are internal information to which I do not have access, which may include IP address of the registered account, voting rings, and spikes in upvotes concentrated in a short period of time.

staff, and is not traceable by external researchers without having access to the actual algorithm. However, the above observation leads to a reasonable proxy for determining the rankings – I count the cumulative number of user upvotes that are not cast by *friends, family, or bots* (FFB). FFB upvotes are defined as upvotes on a particular product by users who registered on the platform no earlier than a day before the product launch and did not upvote any other product during the entire month since registration.

To evaluate how well this proxy captures actual rankings, I compare the actual rankings scraped from archive pages and end-of-launch-day upvotes among a set of 691 recently launched products in September 2018[22]. The Spearman's rank correlation coefficient between actual ranking and *all* cumulative upvotes is 0.8228, while the Spearman's rank correlation coefficient between actual ranking and *non-FFB* cumulative upvotes is 0.8373 which is higher compared to when all upvotes are counted indiscriminately. In this paper, I impute the rankings from *non-FFB* upvotes instead of all upvotes, because the former traces actual ranking more closely and excludes upvotes likely considered spammy by Product Hunt's algorithm.

More precisely, the imputed rank measure is calculated based on the number of non-FFB upvotes received by each featured product on the launch day at 11:59PM (Pacific Time). The majority of organic traffic to Product Hunt ranking feeds are homepage visits, where all of the featured launches on the current day are listed. This means that most of the upvotes are cast on the launch day, and the probability that a product will be viewed by users declines sharply once the launch day ends. Although rankings continue to adjust reflecting cumulative upvotes in real time, the majority of upvoting activity occurs during the launch day, and relative rankings tend to stabilize towards the end of the day. Figure 6 shows that the product rankings are highly persistent after the launch day, and that the correlation between rankings at the end of the launch day and a month after the launch is 0.98 in the sample.

The ranking feed aggregates information about upvotes on products, but they are noisy and susceptible to external shocks and frictions that have nothing to do with the quality of the product or strategy of the startup team. This is because rankings depend not only on the product's own upvotes but also on its *relative* position with respect to all other products also launched that day. For example, when a large technology company such as Google officially announces a product release, it is often immediately shared to Product Hunt as a new product launch, becomes highly upvoted, and takes up a top spot on the launch day ranking feed. This generates an exogenous downward shift to the rankings of startup projects launching on the same day and ranked below the

[22] The real-time rankings were scraped on October 11, 2018.

Google product. The timing of Google's product release cannot plausibly relate to user activities on Product Hunt, since the company is too large to base any strategic decision (such as a product release) on an online platform of a much smaller scale compared to its existing customer base, which is typically a testing ground for less-established firms seeking early adopters.

Another source of friction is the platform's decision to re-launch some products to a future date (often the next day) after they were initially submitted. Anecdotally, makers mentioned that Product Hunt staff reached out to them with suggestions about editing the post to include more information, and guaranteed that their products would be featured on the following day. In other cases, products submitted after 11 AM are likely to be moved to the next day for re-launching, if Product Hunt decides to feature them at all. Re-launched products obtain 11% more cumulative organic upvotes on average, compared to products that are submitted and launched on the same day. This is because re-launched products are often allowed extra time on the ranking feed, as products are usually re-launched at midnight, allowing them maximal exposure to organic traffic during the launch day. They may have also accumulated some upvotes from past days by being on the ranking feed temporarily.

The observations above make it clear that rankings are not strictly determined by products' traction among the user community, nor are they solely due to the quality of the product. The varying amount of time the product is given to be featured on the homepage implies different opportunities of getting organic views and upvotes from users in the community. The process is highly noisy through which the daily rankings are determined, as the length of time during which a product is exposed to organic traffic differs by numerous factors, including timing of the launch and composition of browsing users on the particular day. These differences can occur in artbitrary ways, sometimes depending on the platform's decisions, and sometimes on the startups' launch timing choices – whether they happen to clash with large tech company releases that attract the most user upvotes.

These frictions also provide opportunities for identification. Particular high-impact products released by BigTech[23] and other large companies, as well as decisions made on a case-by-case basis by the platform both shift down the rankings of startup products, in ways unrelated to the quality of the product, or its ex-ante ability to attract user upvotes, with all other things being equal.

3.2 BigTech and Other Large Companies

The first identification approach relies on an instrumental variable constructed from the set of BigTech and other large company launches. In addition to the BigTech firms (Apple, Amazon,

[23] Apple, Amazon, Facebook, Google, and Microsoft.

Facebook, Google, and Microsoft), I consider all public companies that already had an IPO, as well as private companies that raised series B or later rounds (e.g. Stripe) before their products were shared to Product Hunt. These companies must also be frequently mentioned and have many launches highly upvoted on the platform, generating large impact in the user community[24].

The identification assumption requires that BigTech and other large companies' product release decisions are completely unrelated to any considerations about Product Hunt user activity and their products showing up on the platform. This holds because the large companies' product launch strategies are unlikely to involve considerations about Product Hunt. As most of their product releases are shared almost immediately as they are publicly announced, and that the timing of these releases are independent of Product Hunt, these launches create exogenous shifts to the rankings of the rest of the products also launched on that day.

The instrument only counts large firm releases *after* the startup's product has already been submitted, so that the startup firm cannot base their launch decision on these large firm product releases. Companies rarely pull back their launches once Product Hunt features them, and they stay on the same daily product feed as those large company releases which negatively affect their rankings.

3.3 Re-Launched Products

The second identification approach relates to an institutional feature of Product Hunt. On each day, products are submitted and Product Hunt decides whether to feature them on the front page. If the product is selected to be featured, it does not necessarily land on the front page of the day on which it is submitted. Instead, Product Hunt staff may re-launch it on some day in the future, often the next day.

The re-launched products are typically submitted late on the day. Product Hunt rarely features products submitted after 11AM Pacific Time on the same day, which means that conditional on a product submitted after 11AM being featured, its official launch time must be tomorrow or even later[25]. Talking to makers reveals other reasons for a product being re-launched, such as Product Hunt suggesting edits and changes to the post, delaying the official launch.

In the sample, 57% of products were launched on the same day as they were submitted, 32% were re-launched one day after, and 11% were re-launched no less than two days after. The median re-launched products obtained 82 organic upvotes by the end of the launch day, 12% more than

[24] The set of BigTech and large companies for which we measure launch events to include in the calculation of the instrument are public and post-series A companies with at least 10 featured real product launches, which on average obtained 150 or more organic upvotes.

[25] Prior to 2017, Product Hunt may have a slightly different platform policy regarding timing of re-launch.

the upvotes obtained by a median product that was not re-launched. The median ranking of a re-launched product is 11, around 20% higher than the median ranking of 14 of a product that was not re-launched. The re-launched products get more upvotes and become higher ranked, because they stay on the front page for a longer duration of time, and are therefore exposed to more organic traffic from the user community.

Product Hunt decides whether to re-launch a product shortly after the product is submitted, and therefore the re-launch decision cannot depend on any activity that occurs at a future time (e.g. the day after). As long as the startup product's launch date is determined ahead of time, and that other products' maker teams do not pull back from previously planned launches on the same day, re-launching of past products should be an exogenous source of variation in the relative ranking of the product, after controling for common time trends.

3.4 Weighting Products by Predicted Traction

The "frictional" component of the product ranking feed provides an opportunity for identifying the effect of rankings on real outcomes of startups launching products. We can capture the variation in the frictions resulting from high-impact *external* launches by counting the number of such launches that exogenously shift down the rankings of startup products. External launches with more traction potentially shift down rankings of more products, and therefore by making use of additional ex-ante characteristics that are predictive of product traction, we can enhance the instrument and improve the strength of the first-stage relationship without compromising external validity.

The intuition is that that when the external product is potentially more attractive to users, it will end up with more organic upvotes and a higher ranking on the launch day. Therefore, it is more likely to affect the ranking of any startup product that also happens to be featured that day. However, actual upvotes and ranking are endogenous, given that the same set of users are probably viewing the external product as well as startup launches at the same time, the upvoting behavior toward these products will be correlated. The actual upvotes and ranking of external launches are endogenous to activities around startup products launched that day as well.

Therefore, we need to come up with a cleansed version of the external products' traction, which isolates the components that relate solely to the external products' ex-ante potential attractiveness, and *unrelated* to today's new launches. The timing is such that both instruments consist only of information determined *before* the current launch day starts. If we isolate the components of the upvotes on external products that are solely due to characteristics fixed prior to when the external product was officially launched, this should purge the endogenous components of the actual product traction that is due to user activity.

To do this, I use a Poisson model to predict traction of external products, or the number of upvotes that a product will end up with by 11:59 PM (Pacific Time) on the launch day[26]. Inputs to the model include time of submission, product topics, hunter activities in the past, hunter gender and presence of frequent headline keywords, and other ex-ante product characteristics. I augment the training set with "non-featured" products which triples the amount of data, and include whether the product is "featured" as a predictive variable in the model.

The approach works because the potential "traction" of a product is highly predictable by a number of ex-ante characteristics of the product post. Table 4 lists variables that come out of the regularization procedure with non-zero coefficients in most of the training data sets[27], and reports the Poisson regression coefficients and robust standard errors on these variables.

These trained models are then taken to predict traction of products launched in the following year. I calculate the sum of the predicted traction of *external* products, and scale it down by 1,000 for ease of presentation in table format, as the instrument for startup products launched that day that are at risk of being shifted down in rankings.

$$TractionWeightedExternalLaunches_t = \sum_{j \in External(t)} \widehat{Traction}(\boldsymbol{x}^j) \tag{1}$$

Section 4 shows the first-stage relationship between each instrument and imputed product ranking – the endogenous regressor. Instruments for different products launched within the day either assume the same value or are highly correlated, and the major variation in the instruments is at the daily level. Therefore, all regression analyses report robust standard errors clustered by launch date.

3.5 Instrument Validity and Exclusion Restriction

High-impact external products tend to crowd out startup launches and shift down their rankings. External validity of the instrumental variable approach is established if shifts to product rankings induced by high-impact external products are uncorrelated with product quality and maker characteristics. A similar identification strategy is used to examine the effect of the positioning of front page news on stock trading (Fedyk, 2017).

The first external validity requirement is that the actors generating the external launches (e.g.

[26] Upvote counts are non-negative integers, and appear distributed according to the power-law in the data.

[27] Table also shows the optimal regularization parameter, from four sets of training data, each corresponding to all of the submitted products in a given year, e.g. 2014 (which include products launched in 2013 since late November when the platform took shape), 2015, 2016, and 2017.

BigTech and other large companies, and Product Hunt staff that decides to re-launch particular products) act in a way that is not at all influenced by the current startup product launch. This holds for the instrument based on BigTech launches because only those high-impact products launched *after* the given startup product count toward the instrument. This also holds for the instrument based on re-launched products because the re-launch decision is made solely regarding the re-launched product which was submitted on a past day, and prior to the launch of the startup product in consideration. Today's products have not yet been submitted or seen by the Product Hunt staff, when the re-launched products are often relaunched first thing in the morning when today's submissions have not yet rolled in.

The second external validity requirement is that the makers submitting startup products do not time their launches around the sources of information frictions that generate the instruments. It must be that the BigTech launches are not generally known by makers ahead of time. However, these companies typically announce a large number of new product releases during pre-scheduled public events (an exhaustive list of such events includes Apple Special Event, Apple Worldwide Developers Conference, Facebook F8, Google Hardware Event, and Google I/O), and the dates of these events are often made public ahead of time, so that makers should expect many new product releases on those days, and may factor this into their launch timing decision. As a robustness check, I run the regression analysis on a subset of sample products after excluding these publicly available event dates.

It must also be that makers do not cancel planned launches just because Product Hunt had decided to re-launch too many high-impact projects to today's ranking feed. It is quite costly for product teams to reschedule a launch they had planned ahead of time, which involves inviting an external hunter (usually an influencer with a large following on Product Hunt) to coordinate the launch. As robustness chekcs, I restrict the sample to products launched before 1AM (if the makers had been strategic, they should have waited longer to see what other products are being launched on the day and how is competitive the ranking feed), and products with no makers tagged (if posted by external hunters who have no incentive to time the launch).

When a hunter initiates product launches without being in contact with their makers, there is hardly any incentive for him or her to strategically time the launch. The majority of featured products, however, are launched by makers whose strategies can potentially complicate the instruments' validity. For both instruments, I run a placebo test where the outcome is a placebo variable that should be independent of the instrument, otherwise exclusion restriction would be violated. These placebo variable captures whether some makers may have insider information and know in advance when to avoid launching their products.

For example, if the makers have closer connections to the tech communities, they may know what other companies are about to launch products on Product Hunt. If the makers have access to someone who works for Product Hunt, they may be able to influence the internal decision to re-launch their product, or avoid launch days cluttered with other high-impact launches. I use two proxies to measure makers' connections to the tech community (being in a venture capital hub area including the Bay Area) and access to Product Hunt internal information (inviting a Product Hunt employee to hunt the product). I show that the placebo variables are not correlated with the instruments among the set of maker-launched products.

4 Empirical Results

This section describes the empirical results on the impact of information frictions on new venture finance. The basic econometric specification is

$$FundedSeedEarlyStage_{i,t+\Delta T} = \beta_0 + \beta_1 ProductRank_{i,t} + \boldsymbol{b}\boldsymbol{X}_i + \gamma_t$$

Where $\boldsymbol{X}_i$ measures time-invariant product and maker characteristics, and γ_t are time-related controls, specifically year-quarter and day of week fixed effects. The time fixed effects capture time trends that systematically affect both the types of startups launching products and overall rankings of these products.

As discussed in Section 3, the product ranks are measured with noise, imputed based on the ordering of cumulative organic upvotes at the end of the launch day. Because a smaller number indicates a higher rank (e.g. the top ranked product has a rank of 1), I replace the rank variable with minus rank, and report results from running the regression on the flipped ranks.

The unit of observation is a product, launched by startup i during date t. If multiple products are launched during the same week, which are rare situations in which duplicates of the same product are posted more than once, I consider the main launch event to be the one that ends up being featured with the largest number of upvotes at the end of the launch day. Note that the sample is not a balanced panel, because an observation exists only if there is a launch event by the company i during date t. However, companies can launch multiple products at different times on the platform, and hence there may be multiple observations with the same company identifier i in the sample.

4.1 Correlational Evidence and First Stage

I begin by showing the OLS relationship between the endogenous regressor and funding outcome. Figure 7 plots the average funding probabilities for products in each rank bucket from 1–5, 6–10, 11–20, 21–30, and below 30. Being ranked daily top 5 is associated with a3.5% probability of announcing a seed or series A funding round within 6 months of the product launch, 1 percentage point higher than the average funding probability of products ranked from 6–10.

Higher ranks are associated with larger probabilities of securing seed and early-stage funding. There can be as many as 60 featured products launched on a given day, although the lengths of most ranking feeds range between 20 and 40 products. Each downward shift in rank is associated with less funding for seed and early-stage startups, and the magnitude of the change in funding probability declines with lower rankings. The probability of being funded is 1.6% among products ranked 21–30, only 0.8 percentage points lower than that of products ranked 11–20.

However, the correlation between product rankings and funding outcomes may be due to unobserved common factors, such as the the product being of higher quality, and therefore getting more user upvotes and being ranked higher, which also correlates with larger need for capital to grow the customer base and greater success at fundraising. To identify a causal relationship between the endogenously determined rankings and the company's post-launch fundraising outcome, I use two sets of instrumental variables to isolate shifts to product rankings unrelated to quality of the product and characteristics of its makers. The instrumental variables measures the "frictional" components in the products' rankings. Section 3 contains a thorough explanation of the construction and exogeneity of the instruments. While being unaffected by any ex-ante covariates of the economics of the startup, changes in product rankings induced by the instruments end up affecting downstream outcomes of startup companies, including their ability to raise seed and early-stage funding. A potential mechanism is that these rankings should affect the product's visibility and status, by changing how information is presented and digested on the platform.

I estimate the first-stage relationship in the following regression.

$$ProductRank_{i,t} = \alpha_0 + \alpha_1 TractionWeightedExternalLaunches^{K}_{i,t} + \boldsymbol{a}\boldsymbol{X}_i + \xi_t$$

Where $K \in \{BigTech, ReLaunch\}$ for the two sets of instruments, respectively. Then I use the predicted regressor $\widehat{ProductRank}_{i,t}$ to estimate the second stage.

$$FundedSeedEarlyStage_{i,t+\Delta T} = \beta^{IV}_0 + \beta^{IV}_1 \widehat{ProductRank}_{i,t} + \boldsymbol{b}^{IV}\boldsymbol{X}_i + \gamma^{IV}_t$$

Figure 8 illustrates the first-stage relationship between the instruments and the endogenous regressor. The left panel plots the first-stage regression results for the first instrument, based on BigTech and other large firms' product releases; the right panel plots the first-stage regression results for the second instrument, based on re-launched products from past days. Both panels are binned scattered plots of the instrument against residual rankings after removing time trends (i.e. launch hour, day-of-week, and year-quarter fixed effects), and the standard errors are clustered at the launch date level. Table 5 presents the first-stage coefficient estimates and goodness-of-fit statistics for both instruments on the final analysis sample. Columns 2 and 4 include hunter, maker and post control variables, where the estimates suggest stable first-stage relationships. These results rule out weak instruments, and therefore establish that IV estimation is unbiased for both instruments.

4.2 Effects of Product Ranks on Seed and Early-Stage Funding

The regression sample consists of product launches of private companies which have not yet raised series B rounds or beyond, and were founded no more than 5 years prior to the launch event. The sample includes all technology product launches from the beginning of April 2015 to the end of March 2018 by companies that fit these criteria[28].

These product launches are linked to companies' CrunchBase profiles through the website URL, and I use extracted domain names in the URLs to uniquely identify companies[29]. The final sample consists of 23,119 product launches by 20,508 unique startup companies. The average probability of a sample company obtaining seed or series A funding is 2.43% within 6 months. The median product rank is 13, and the 95th percentile of product rank is 33. Table 3 shows the breakdown of funding announcements by type of funding and number of months since launch, for products ranked above median and below median, respectively.

Table 6 reports the effects of product rankings on startups' fund raising outcomes. The outcome variable is whether the startup has raised seed or series A round within 6 months of launching a product, and the endogenous regressor is the imputed ranking of the product on the launch day front-page feed. Results in Panel A are estimated using an instrument based on BigTech and other large firms' product releases *after* the current product launch, and results in Panel B are estimated using an instrument based on the platform's decision to re-launch particular

[28]Podcast episodes, books, games, and other non-technology product posts are not included in the sample, as are projects hosted by a third-party website and not a standalone company. Sample construction is described in Section 2.

[29]The unique identifier of a company's website consist of the top-level and second-level domains of the URL, and I match CrunchBase profiles to Product Hunt posts through the identifier.

products submitted in the past. OLS estimates are reported in column 1 of both panels to compare with IV/2SLS estimates.

When the ranking of a product is shifted down by 1 due to *external* products consisting the instruments, the funding probability within the next 6 months declines by between 0.13 and 0.39 percentage points, or between 5.3% and 16% upon the average probability of 2.43%. The seemingly wide range of the estimates belie the fact that products are affected differentially by the change in ranking, depending on their rank position. For example, a product ranked among the daily top 5 are disproprotionately more affected compared to a product ranked 30th on the launch day. The estimates are robust to adding controls for hunter, maker and post characteristics, reported in column 3 of both panels. All specifications control stringently for time trends by including launch hour, day of week, and year-quarter fixed effects.

In Panel A of Table 6, column 4 presents the coefficient estimates on a subsample of products launched on days without a BigTech pre-announced event. In Panel B of Table 6, column 4 presents the coefficient estimates on a subsample of products submitted before 1AM Pacific Time, and column 5 presents the coefficient estimates on a subsample of products that do not tag a maker. The results in these columns are similar to those estimated using the same instruments but without the sample restrictions, suggesting that the estimated effects are not explained by omitted common factors related both to external launches consisting the instruments and to startups' post-launch real outcomes. This is evidence that *external* launches consisting the instruments indeed induce frictions in the rankings that are neither undone by the platform nor counteracted by makers' strategic choices, and that they lead to real consequences on startups' fundraising outcomes.

It is worth noting that the coefficients estimated from the BigTech instrument are almost three times the size of the coefficients estimated from the re-launch instrument. This is due to higher ranked products being disproportionately more affected by shifts to their rankings than lower ranked products. The median rank of external launches that consist the BigTech instrument is 7, higher than the median rank of 11 among external launches that consist the re-launch instrument. About 40.6% of the BigTech external launches are ranked among the daily top 5 products, compared to only 23.7% of the re-launches. If shifts to rankings especially affect products that are ranked among the top, then the coefficient estimates on these top products should be disproprotionately large.

The instrumental variable regression estimates the local average treatment effect of the endogenous regressor on the part of the regressor that is shifted by the instrument. Because the effect of rankings may be largely different for products at different places in the ranking, the IV strategies can lead to largely different estimates of the local average treatment effect, depending on which part of the rankings are most susceptible to being shifted by the particular instrument.

For example, an external re-launch that ends up the 10th product of the day will not move the ranks of products with more organic upvotes and hence ranked above the 10th place, and therefore the first stage does not shift these products' rankings. On average, the BigTech instrument shifts rankings of products that are higher ranked than the re-launch instrument. If it is indeed the case that highly-upvoted products are disproportionately more affected by shifts to their rankings, then the local average treatment effect recovered from the BigTech instrument should be larger than that recovered from the re-launch instrument, as is evidenced by comparing the two panels in Table 6.

To quantify the magnitude of the effect of rankings in different parts of the spectrum of rank positions, I run an instrumental variable regression of the following specification, in which M_t denotes the median rank among products launched on a given date t.

$$FundedSeedEarlyStage_{i,t+\Delta T} = \beta_0 + \beta_1^l \mathbb{1}(Rank_{i,t} < M_t) Rank_{i,t} + \beta_1^h \mathbb{1}(Rank_{i,t} \geq M_t) Rank_{i,t} + \boldsymbol{b}\boldsymbol{X}_i + \gamma_t$$

Table 7 presents IV estimates of this specification, focusing on the effect of rankings for products in the bottom half and top half of the daily feed respectively. Columns 2–3 use the BigTech instruments and columns 4–5 use the re-launch instrument to estimate the differential effects of rankings, and both approaches yield comparable coefficient estimates and effect sizes for below median and above median products respectively. Among products ranked median or above on a given launch day, each rank being shifted down lowers funding probability by 0.37–0.41 percentage points, which is equivalent to a 12.5%–13.9% decrease in funding probability from the baseline average. Among products ranked below median on a given launch day, each rank being shifted down lowers funding probability by about 0.09 percentage points, which is equivalent to a 4.8% decrease in funding probability from the baseline average. These results reconcile the largely different magnitudes of the local average treatment effect estimates between the two sets of instruments in Table 6.

4.3 Mechanism and Robustness Checks

There are two different channels through which the rankings of product launches can affect real outcomes. First, the rankings affect the visibility of products, and whether users are going to view the product description, spend time navigating the product page, and click on the upvote button. The top ranked products are more likely to get users' attention, and the users may need to scroll down to even notice the lower ranked products and hence less likely to click through and browse further. This also affects the opportunity to get upvotes from users. Depending the device being used to access the Product Hunt platform, lower-ranked products can be less visible on the Product Hunt mobile app than they are on the website.

Appendix Table A1 presents IV results on the effect of shifts to product rankings on organic upvotes accumulated by 11:59PM Pacific Time on the launch day. Column 1 reports the OLS coefficients for comparison. Columns 2–3 present estimates based on the BigTech instrument, and columns 4–5 present estimates based on the re-launch instrument. Each product loses 4–5 upvotes on average from being shifted down 1 rank by the instruments, which is a substantial 30–40% of the mechanic association between the number of upvotes and rankings benchmarked by the OLS coefficient estimate. Each of these user upvotes may convert into word-of-mouth and external demand that is not measured in the paper, but nevertheless a plausible channel through which the effect of Product Hunt information is further magnified by offline activities and end up influencing outcomes in the real economy.

Second, the rankings can affect real outcomes directly by being a direct status signal of the startup. If a product achieves top ranking on a given launch day, it could directly add this information to its pitch deck. The media is more likely to pick up this information, generating more external demand through news coverage. The empirical finding in Table 7 aligns with such a mechanism, where the effect of ranking is especially pronounced among top-ranked products. Section 5 attempts to provide further evidence on this channel.

Because upvotes are also visible on the website, they may directly affect startups' outcomes. To gauge the relative importance of upvotes vis-á-vis rankings, Appendix Table A2 shows results from running a horse race between product ranking and organic upvotes for their relative impact on funding probability within 6 months. Column 1 and 2 present OLS results on the correlation between organic upvotes and post-launch 6-month funding probability without and with product ranking as a control variable, respectively. The OLS coefficient on organic upvotes shrinks from being significant to zero after controling for product ranking. The IV estimates also suggest the significant effect of product rankings, which is not altered much after controling for organic upvotes. These results suggest the robust effect of ranking on its own, that are above and beyond the direct impact of upvotes on funding outcome.

It is plausible that neither are BigTech launches affected by startups' product launch strategy on Product Hunt, nor does Product Hunt re-launch products based on holistic consideration about expected future launches. These assumptions rule out major concerns about the external validity of each of the instruments from the perspective of the economic actors who generate these external launches. There remains a concern about how makers may be able to *preempt* and/or *react to* external launches. If some makers could indeed preempt the external launches and adjust their strategies accordingly in advance, then the instrumental variable's exclusion restriction would be violated. If this were true, then makers with better information and closer connection to Product Hunt internal staff must be more likely to avoid cluttered launch dates and high-impact competition from the external launches that consist the instruments.

Appendix Table A3 rules out such a possibility. Launches with varying traction-weighted external competition are not more or less likely to be hunted by Product Hunt staff and early members (who are given special thanks on the website's info page), as the non-significant coefficients suggest in columns 1–4. Columns 5–8 suggest that maker teams located in top venture capital destinations (San Francisco Bay Area, New York City, London, and Boston), which host the most vibrant tech innovation eco-systems, are not more or less likely to avoid competitive external launches or cluttered ranking feeds. These results suggest that the instrumental variable strategy is robust to the concern about makers strategically timing the launch when they are more informed or connected to the tech community or platform insiders.

5 Discussion of Mechanisms

5.1 A Simple Model of Information Acquisition

I derive a simple theoretical framework to explain startups' and early investors' decisions. In this framework, entrepreneurs and investors observe a series a signals realized over time about the profitability of a venture. In the canonical model of Jovanovic (1982), new firms learn about their efficiency after entering an industry and endogenously choose to continue operating or close down in each time period, based on the expected NPV of future profits.

In my framework, not only do entrepreneurs decide whether to continue developing the project or move on to other paths based on the realized signals, which becomes an input to generating the signal in the next period, but investors also observe the signals and incorporate them into investment decisions. The framework has a flavor of the statistical discrimination model (Aigner and Cain, 1977), in which decisions are made over coarse priors of the group average over observable traits, before more and more signals become gradually revealed to differentiate individual ability.

During each time period $t = 0, 1, \ldots, T$, investors learn about the potential product profitability θ by obtaining a noisy Gaussian signal η_t. Higher profitability firms with larger θ will have on average higher signals in each time period through $\eta_t = \theta + \epsilon_t$ where ϵ_t are time-specific shocks with Gaussian distribution $N(0, \sigma_t^2)$, independent over time and across firm. The productivity translates into realized profits x_t through a known link function $x_t = \xi(\eta_t)$ at time t, which is linear and strictly increasing.

After receiving signals for T time periods, the investor's belief about a startup firm's profitability θ can be expressed by a Gaussian posterior $p\left(\theta|\{\eta_t, \sigma_t^2\}_{t=0}^T\right) \sim N(\bar{\eta}_T, \bar{\rho}_T^{-1})$. Denote precision ρ_t as the inverse of variances $\rho_t = \sigma_t^{-2}$ of signals in each time period. It is easy to show that these relevant parameters are sufficient statistics calculated from signals in each period.

$$\bar{\eta}_T = \left(\sum_{t=0}^{T} \rho_t\right)^{-1} \sum_{t=0}^{T} \rho_t \eta_t, \quad \bar{\rho}_T = \sum_{t=0}^{T} \rho_t \tag{2}$$

An additional signal always increases the precision (lowers the uncertainty) in updated belief as $\bar{\rho}_T - \bar{\rho}_{T-1} = \rho_T > 0$ for any T. Precision ρ_t of signal at time t correspond to the weight placed on signal η_t in the expectation of $\bar{\eta}_T$.

The entrepreneurial companies at seed and early stage face high uncertainty in their future prospects. When ex-ante uncertainty about a product's profit potential is larger, this model suggests that ρ_T is smaller and that an additional signal updates the investor's belief about the startup's profit potential to a larger extent. The ρ_T's are different across companies, as the informativeness of the sum of prior signals differ among them.

When companies launch products on Product Hunt, the launch day rankings provide an additional signal about their potential profitability. Launching a product that ends up with a higher ranking signals product traction, and various stakeholders including entrepreneurs themselves, potential customers as well as investors react to this additional piece of information.

Before launching products on Product Hunt, startups have different baseline statistics, summarized as a prior distribution over $\theta \sim N(\bar{\eta}_T, \bar{\rho}_T^{-1})$. The launch day rankings generate a new signal $\tilde{s}$, which is believed to have the following structure, where $\iota \sim N(0, \rho_\iota^{-1})$.

$$\tilde{s} = \theta + \iota \tag{3}$$

The posterior belief after incorporating the new Product Hunt signal is normally distributed as

$$\theta|\tilde{s} \sim N\left((1-\lambda)\bar{\eta}_T + \lambda\tilde{s}, \lambda\rho_\iota^{-1}\right) \tag{4}$$

where $\lambda = \frac{\rho_\iota}{\bar{\rho}_T + \rho_\iota}$ measures the relative precision of the new signal. Intuitively, $\bar{\rho}_T^{-1}$ is a measure of uncertainty among investors over a startup's profit potential. Larger uncertainty in the baseline is reflected by lower precision $\bar{\rho}_T$ after the investor aggregates all signals generated prior to the Product Hunt launch. As a direct result, investors put more relative weight on the new signal when ex-ante uncertainty is larger over the startup's future prospects.

There are many reasons that Product Hunt rankings may be noisy and the signal prone to bias, since it requires no commitment and barely any cost (except for logging into the website as a registered user) to upvote products. Therefore, the true data generating process of $\tilde{s}$ is different and contains a "frictional" component Δ

$$\tilde{s} \sim N(\theta_0 + \Delta, \rho_\Delta^{-1})$$

where θ_0 is the actual parameter governing the profitability of the firm, and Δ is the bias term due to information frictions. The marginal distribution of the posterior belief, integrated over the range of realizations of $\tilde{s}$ can be written as

$$\int \theta(\tilde{s}) dp(\tilde{s}) \sim N\left((1-\lambda)\bar{\eta}_T + \lambda(\theta_0 + \Delta), \lambda\rho_\iota^{-1} + \lambda^2\rho_\Delta^{-1}\right) \tag{5}$$

Suppose that the risky venture can achieve two payoff possibilities, one where it exits with large success returning the equity of w, and the other where it fails or barely subsists without returning the investors anything. The profitability parameter θ translates into success probability through a link function $\xi(\cdot)$ strictly increasing and bounded between 0 and 1, and the investor chooses to invest if expected return is greater than or equal to outside option with payoff equal to c. Investors are heterogeneous with different outside options so that c is normally distributed with mean μ_c and variance ρ_c^{-1}, and there is a continuum of them with measure 1. μ_c is much smaller than w so that $\Phi^{-1}(\frac{\mu_c}{w}) \ll 0$.

A rational investor should choose to invest (denoted as the investment decision $y = 1$) if and only if $E\left[w \cdot \xi(\theta(\tilde{s}))\right] \geq c$. Denote $\Phi(\cdot)$ the cumulative density function and $\phi(\cdot)$ the probability density function of the a standard normal random variable. A convenient choice of $\xi(\cdot)$ is such that $\xi(\theta) = \Phi(\alpha\theta)$, which reduces the investor's decision criterion to

$$w \cdot \Phi\left(\frac{\alpha(1-\lambda)\bar{\eta}_T + \alpha\lambda\tilde{s}}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}}\right) \geq c \tag{6}$$

Therefore, the investment probability can be written as

$$Pr(y=1) = \Phi\left[\left(w \cdot \Phi\left(\frac{\alpha(1-\lambda)\bar{\eta}_T + \alpha\lambda\tilde{s}}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}}\right) - \mu_c\right)\sqrt{\rho_c}\right] \tag{7}$$

which is apparently strictly increasing in $\tilde{s}$ and in $\bar{\eta}_T$. Empirically, the probability of getting seed and early-stage venture investment is extremely low, so that we can safely assume $Pr(y = 1) < 0.1$. In the Product Hunt sample, the probability of getting seed or early-stage funding within 6 months is less than 3%. This implies

$$\frac{\alpha(1-\lambda)\bar{\eta}_T + \alpha\lambda\tilde{s}}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}} < \Phi^{-1}\left(\frac{\mu_c}{w}\right) \tag{8}$$

Because it is assumed that $\Phi^{-1}(\frac{\mu_c}{w}) \ll 0$, these inequalities together imply that the realistic range of parameters are such that $x = \frac{\alpha(1-\lambda)\bar{\eta}_T+\alpha\lambda\tilde{s}}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}} \ll 0$, and hence on the convex part of $f(x) = \Phi\left[(w \cdot \Phi(x) - \mu_c)\sqrt{\rho_c}\right]$ as a function of x. Now the size of the effect $\beta = \frac{\partial Pr(y=1)}{\partial \tilde{s}}$ of $\tilde{s}$ on funding probability $Pr(y = 1)$ can be written as

$$\beta(\tilde{s}, \bar{\eta}_T, \lambda) = f^{'}\left(\frac{\alpha(1-\lambda)\bar{\eta}_T + \alpha\lambda\tilde{s}}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}}\right)\frac{\alpha\lambda}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}} \tag{9}$$

Consider the comparative statics on the relative effect sizes for different types of ventures, captured by the parameters $\tilde{s}$, $\bar{\eta}_T$, and λ. The effect size β increases both in $\tilde{s}$ and in $\bar{\eta}_T$ because

$$\frac{\partial\beta(\tilde{s}, \bar{\eta}_T, \lambda)}{\partial\tilde{s}} = f^{''}\left(\frac{\alpha(1-\lambda)\bar{\eta}_T + \alpha\lambda\tilde{s}}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}}\right)\frac{\alpha^2\lambda^2}{1+\alpha^2\lambda\rho_\iota^{-1}} \tag{10}$$

$$\frac{\partial\beta(\tilde{s}, \bar{\eta}_T, \lambda)}{\partial\bar{\eta}_T} = f^{''}\left(\frac{\alpha(1-\lambda)\bar{\eta}_T + \alpha\lambda\tilde{s}}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}}\right)\frac{\alpha^2\lambda(1-\lambda)}{1+\alpha^2\lambda\rho_\iota^{-1}} \tag{11}$$

are both greater than 0. Now consider conditions under which the effect size β increases in λ, holding all else constant (including and especially ρ_ι).

$$\frac{\partial\beta(\tilde{s}, \bar{\eta}_T, \lambda)}{\partial\tilde{s}} = f^{'}\left(\frac{\alpha(1-\lambda)\bar{\eta}_T + \alpha\lambda\tilde{s}}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}}\right)\frac{\alpha + \frac{1}{2}\alpha^3\lambda\rho_\iota^{-1}}{(1+\alpha^2\lambda\rho_\iota^{-1})^{\frac{3}{2}}} \tag{12}$$

$$+f^{''}\left(\frac{\alpha(1-\lambda)\bar{\eta}_T + \alpha\lambda\tilde{s}}{\sqrt{1+\alpha^2\lambda\rho_\iota^{-1}}}\right)\frac{\alpha^2\lambda\left[(\alpha^2\lambda\rho_\iota^{-1}+2)(\tilde{s}-\bar{\eta}_T) - \alpha^2\bar{\eta}_T\rho_\iota^{-1}\right]}{2(1+\alpha^2\lambda\rho_\iota^{-1})^2} \tag{13}$$

It is straight-forward to show that there exists δ such that $\tilde{s} - \bar{\eta}_T \geq \delta$ is a sufficient condition of $\frac{\partial\beta(\tilde{s},\bar{\eta}_T,\lambda)}{\partial\tilde{s}} > 0$. This holds by letting $\delta = \frac{\alpha^2\bar{\eta}_T\rho_\iota^{-1}}{\alpha^2\lambda\rho_\iota^{-1}+2}$.

Product Hunt selectively featuring products makes this condition likely to hold, as the featuring decision can be seen as "screening" of product posts so that the signals are visible only among products with the largest $\tilde{s}$. Product Hunt features only about a third of daily submissions. If

$\Delta \geq 0$ as far as makers' strategies are concerned, the distribution of $\tilde{s} - \bar{\eta}_T$ (before screening) should be normally distributed with a non-negative mean. When the priors are coarse enough and priors very conservative, $\lambda \to 1$ and $\bar{\eta}_T \ll 0$ is almost uninformative and similar across all products. If screening is effective, so that only the products with the largest $\tilde{s}$ are "featured", and products with $\tilde{s} < \bar{\eta}_T$ would not be featured, then the condition $\tilde{s} - \bar{\eta}_T \geq \delta$ must hold among "featured" and hence ranked products.

5.2 The Value of Rankings to Entrepreneurs, Consumers and Investors

Conversations with makers on Product Hunt reveal at least three mechanisms through which product rankings affect startups' real outcomes.

First, the entrepreneurs learn about the potential appeal of their own product ideas. Makers come from a diverse range of backgrounds, and some of them launch side projects on the platform, and invite public attention to their creations for the first time. Receiving positive feedback from the Product Hunt community increases the likelihood that they would continue to develop their ideas (often prototypes), which increases the chance that the product would evolve into a full-fledge company, and that the makers would seek external investors to help grow the business. Some people may become entrepreneurs because Product Hunt provides them with an opportunity to publish their projects and acquire early-adopters, which may otherwise be difficult barriers that prevent makers from becoming entrepreneurs in the first place.

Second, top-ranked products are visible to potential consumers. Often, a spike in traffic to the product website follows the launch event on Product Hunt. These website views then convert into product sign-ups. Since the Product Hunt community primarily consists of early adopters and influencers, who are often product enthusiasts that generate word-of-mouth through talking to friends, colleagues, and social media. This amplifies the effect of the rankings on user acquisition and future sales.

Last but not least, the rankings are direct signals that entrepreneurs can include in their pitch decks as proof of product traction to investors. Especially when the product is highly upvoted and ranked among the top, the Product Hunt certification makes a strong case for product-market fit, among factors taken into account by early-stage investors in valuing startups and making investment decisions.

All three mechanisms can impact fundraising of the launching startups, either directly or indirectly. This paper does not separate amongst these mechanisms but leave the task to future work, which requires decent measurement of intermediate outcomes including startup survival, entrepreneurs' strategic choices, and product sales.

5.3 Empirical Tests of the Information Mechanism

A direct implication of the theoretical framework in Section 5.1 is that the Product Hunt rankings should induce greater information updating by startups that are ex-ante more opaque. When stakeholders such as investors have less prior knowledge about a company, they are more likely to update their beliefs based on Product Hunt's ranking signals.

Investors may pass on an investment for two fundamentally different reasons. For one thing, there may be too much risk involved in investing in a venture that lack enough information to assess its potential. For another, it may be that the observed traits of the company and its founder team do not meet the threshold for investing. In the highly uncertain environment of entrepreneurial ventures and seed investing, it is very common for there to exist information frictions and insufficient data about a new venture.

Both social and geographical proximity alleviate the information gap, but when startups are far away from or lack connections to the investors, they face higher barriers to accessing funding, while at the same time Product Hunt rankings should have a larger impact on their fundraising success as explained in the theoretical framework. When it is due to the lack of information to sufficiently predict the outcome of the new venture or high variance on future returns that investors pass on the investment, the data should exhibit differentially larger effects of Product Hunt rankings on fundraising probability.

Table 8 presents evidence that rankings differentially affect products that differ in geographic proximity to venture investors. The sample is split into maker teams that have at least one member located in one of the VC hub areas and the rest of the maker teams[30]. The table shows results from running an instrumental variable regression of the following specification. Column 1 reports OLS coefficients for comparison.

$$FundedSeedEarlyStage_{i,t+\Delta T} = \beta_0 + \beta_1^{non}\mathbb{1}(NotHub_i)Rank_{i,t} + \beta_1^{hub}\mathbb{1}(Hub)Rank_{i,t} + \boldsymbol{bX}_i + \gamma_t$$

The IV estimates reveal that shifts to product rankings induced by the instrument have negligible impact on the fundraising probability of startups located in top VC destinations (more precisely, when at least one of the makers is located in the hub area), despite the positive correlation suggested by the OLS coefficients. On the other hand, startups located outside the hub areas are significantly affected by shifts to product rankings induced by the instrument. Each rank is

[30] The first definition of a hub area includes top venture capital destinations – or the regions with the laregest deal volumes between 2015 and 2018, and account for over 50% of all seed and series A rounds worldwide in the CrunchBase data. The top destinations include San Francisco Bay Area, New York City, Boston and London.

associated with changes in 6-month's funding probability by 0.2 percentage points (or about 10% upon the average probability of 2%) among non-hub startups.

Startups that are located in hub areas face lower ex-ante barriers to accessing venture investors. While Bernstein et al. (2016) documents the cost of traveling to VC monitoring their existing portfolio companies, a similar mechanism should predict a positive correlation between geographic distance and cost to screening potential investments. Evaluating companies is less costly when the startups based in proximity to the destinations where the VCs are also located or to which the VCs often travel.

In the hub areas, VCs can gather information from more alternative sources other than Product Hunt to learn about the startup and its founders. Also, there may be abundant funding available in these areas and more channels to access investors, and hence the non-effect of shifts to rankings on funding probability of startups located in the VC hubs. On the other hand, startups located outside the hub areas are affected by their product rankings, because investors have relatively few alternative information signals about the companies, and Product Hunt rankings weigh more into the consideration in place of missing alternative sources.

Table 9 presents evidence that rankings differentially affect products created by teams with female makers versus all-male maker teams. The table shows results from running the instrumental variable regression of the following specification. Column 1 reports OLS coefficients for comparison.

$$FundedSeedEarlyStage_{i,t+\Delta T} = \beta_0 + \beta_1^f \mathbb{1}(SomeFemale_i)Rank_{i,t} + \beta_1^m \mathbb{1}(AllMale)Rank_{i,t} + \boldsymbol{b}\boldsymbol{X}_i + \gamma_t$$

To the extent that female founders and product makers have fewer connections to venture investors and the VC industry, these results confirm the mechanism discussed in section 5.1. The product rankings affect funding probability of startup teams with female members much more than those with only male members. Female-present teams and male-only teams achieve about the same median and mean rankings across the sample, while the average funding probability in 6 months among teams with female members is 4.4%, about 1.8 times the average funding probability of male-only teams. These results may mask the fact that female makers select into Product Hunt differently than male makers, and that the female teams on average have better funding prospects. But on top of the differences in average fundraising across gender, product rankings have a larger effect on female teams' fundraising success than male-only teams.

These results have additional implications for digital entrepreneurs' access to seed and early-stage investors. The startups for which information spreads less easily coincide with those that face more difficulty raising money or getting connected to potential investors. Therefore, an online platform like Product Hunt, which aggregates information from an early adopter community, may bridge existent gaps in digital entrepreneurs' access to capital.

6 Conclusion

To summarize, the paper explores the unintended consequences of shifts to product rankings on Product Hunt due to external launches uncorrelated with the current product's quality or startup team's characteristics. I show that an exogenous downward shift to the rank of a Product Hunt featured product lowers the chance of the startup raising seed (including convertible note) and series A rounds within 6 months by 0.23 percentage points, or a 9.5% decline relative to the average funding chance of 2.43%.

The effects are mainly driven by product teams located outside top venture capital destinations such as San Francisco, New York, London, and Boston. Product teams with female members are more affected by shifts to these rankings compared to all-male teams. Product Hunt improves access to venture capital among startups that may otherwise lack an opportunity to reach investors, by giving them a chance to have their products prominently featured and ranked top in a product feed updated daily to reflect the latest technology products on the startup market.

The effects are more nuanced, as higher ranked products are disproportionately more affected by the shifts to rankings than lower ranked products. The differential effects on funding outcome by rank position suggest that user attention may concentrate on the top products, and winners of these daily launch feeds may enjoy benefits that accrues more rapidly with ranking than predicted by a linear function.

The information acquisition framework applies to this setting for three types of stakeholders – entrepreneurs, consumers, and venture investors. Product rankings can influence each of these stakeholders, which directly and indirectly affect downstream startup outcomes and choices, including fundraising and other variables such as startup survival, product sales, and strategic decisions. This provides some scope for future work to further investigate these channels separately.

The rankings matter for both the *visibility* and *status* of the product. Whereas the former leads to more attention from prospective customers and investors, the latter directly attracts influencer word-of-mouth and tech media coverage, and helps entrepreneurs make their case for product-market fit while pitching to venture capital investors.

Future work may focus on other intermediate startup outcomes such as survival and product sales, as well as entrepreneurs' strategic choices such as deciding the best next move for expanding the market to sell the product. It may also be worthwhile studying not only the total upvotes toward a product on the platform, but also the *composition* of these upvotes. Do entrepreneurs learn about their market fit through information about *who* likes their products, and not just how many people like their products?

More generally, the paper introduces a novel data source to study digital entrepreneurs' product launch strategy on an online platform, and the real effects of information frictions induced by the way in which the platform is designed, including downstream outcomes such as seed and early-stage fundraising. The data will be useful to future research on digital innovation, to examine the interaction between digital entrepreneurs and the product market they serve.

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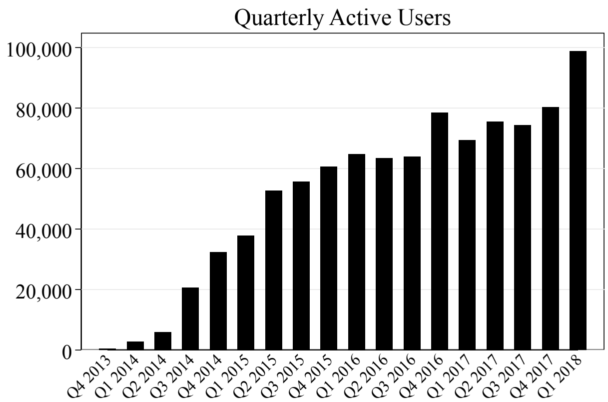
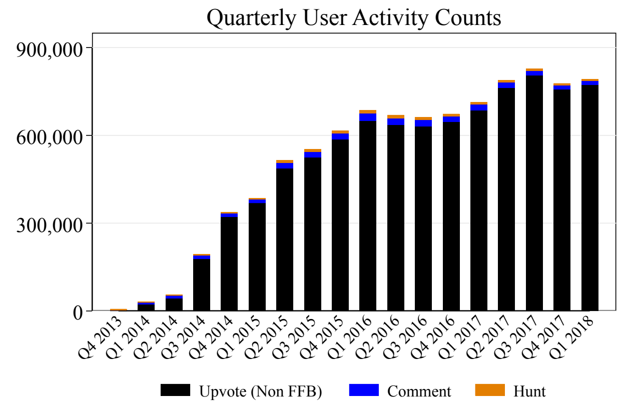
Figure 1: Time Trends in Number of Active Users and User Activities (up to end of 2018Q1)

(A) Number of Active Users

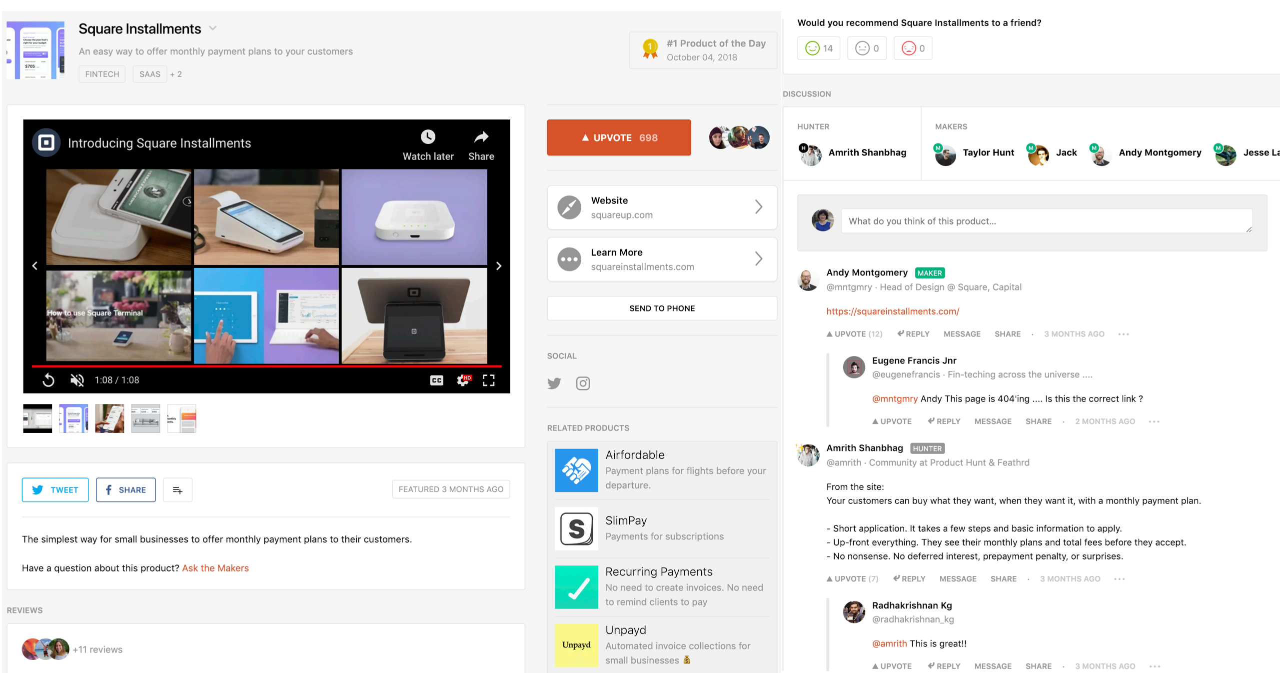


(B) Number of User Activities by Activity Type



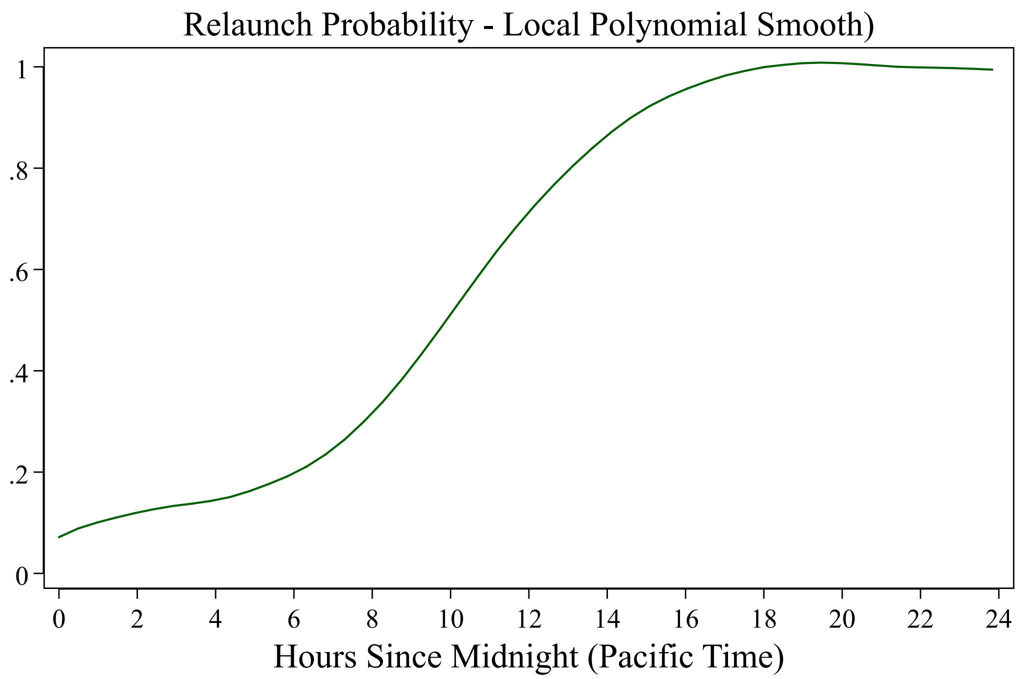
Notes: Figures show time trends in the number of active users and user activities from Product Hunt inception to the end of the 1st quarter of 2018. Active users are defined as those who have participated in at least one of the following activites: hunting a product, commenting on a product, and upvoting a product which must not be a family, friend, or bot (FFB) upvote. Subfigure (A) shows the growth in the number of active users, and subfigure (B) shows the growth in the total amount of Product Hunt activity by type of activity.

Figure 2: Product Launch Example – Square Installments



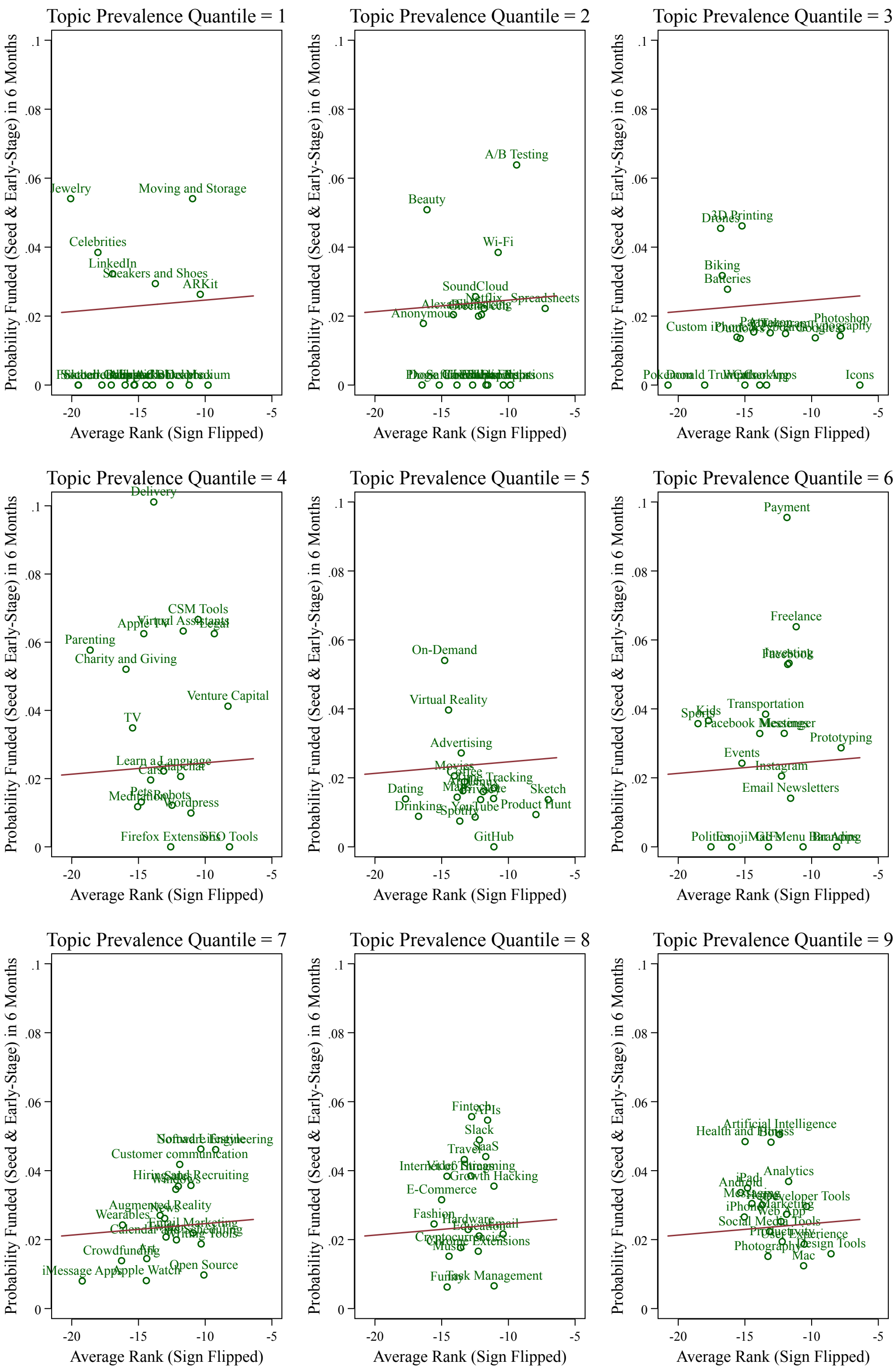
Notes: Figure shows screenshot of the launch page of Square's latest product – Square Installments, featured and top-ranked on Product Hunt on October 4, 2018. detailed description of product is shown to the left, and comment section with hunter and maker information is shown to the right.

Figure 3: Featured Products Re-Launch Probability by Submission Time of Day



Notes: Figure shows the evoluation of the probability of a featured product being re-launched on the next day by time of submission, starting at midnight (in Pacific Time) of the launch day.

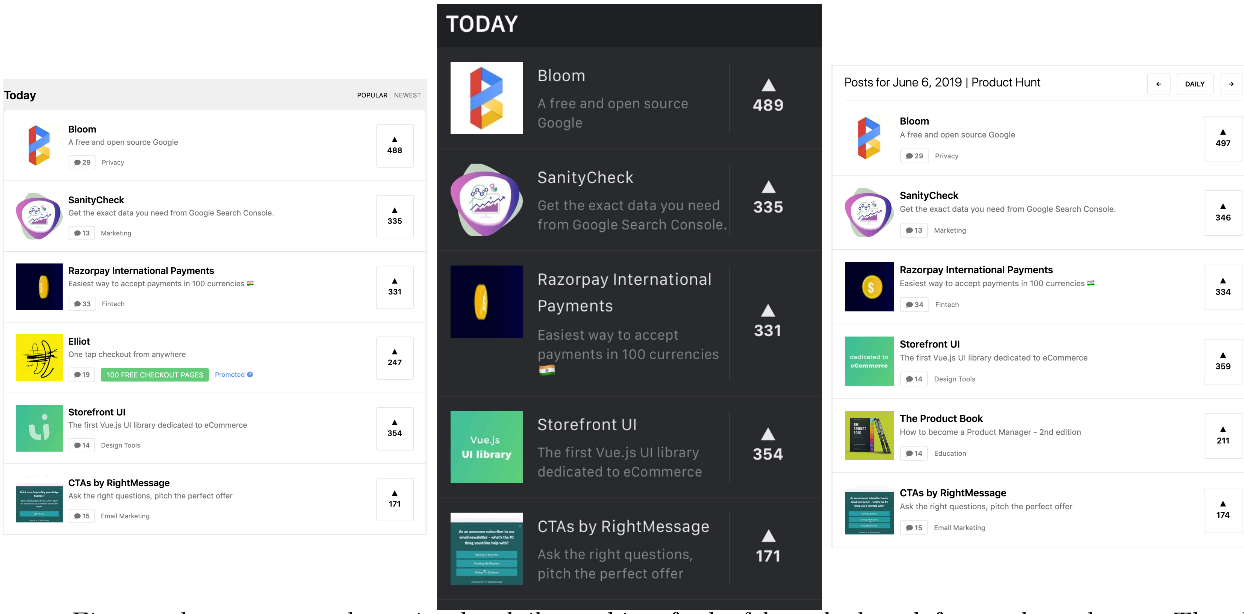
Figure 4: Product Traction by Topic Prevalence (Nine Quantiles)



Notes: Figure shows the median number of non-family, friend or bot upvotes that products get by the end of the launch day, for each tagged topic that are associated with at least 25 products in the analysis sample. These topics do not include "Tech" (which is tagged for over 85% of products, and almost all products are assumed to be related to tech by Product Hunt definition).

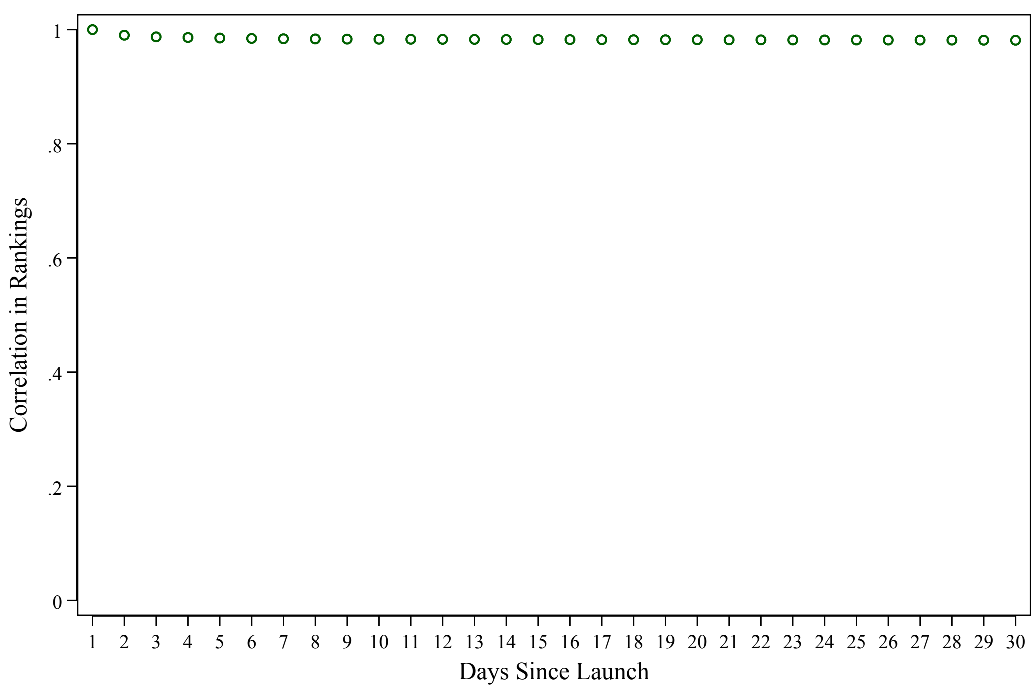
Figure 5: Top Launched Products in Daily Ranking Feed

(A) Today – Desktop **(B)** Today – iPhone App **(C)** Time-Travel – Desktop



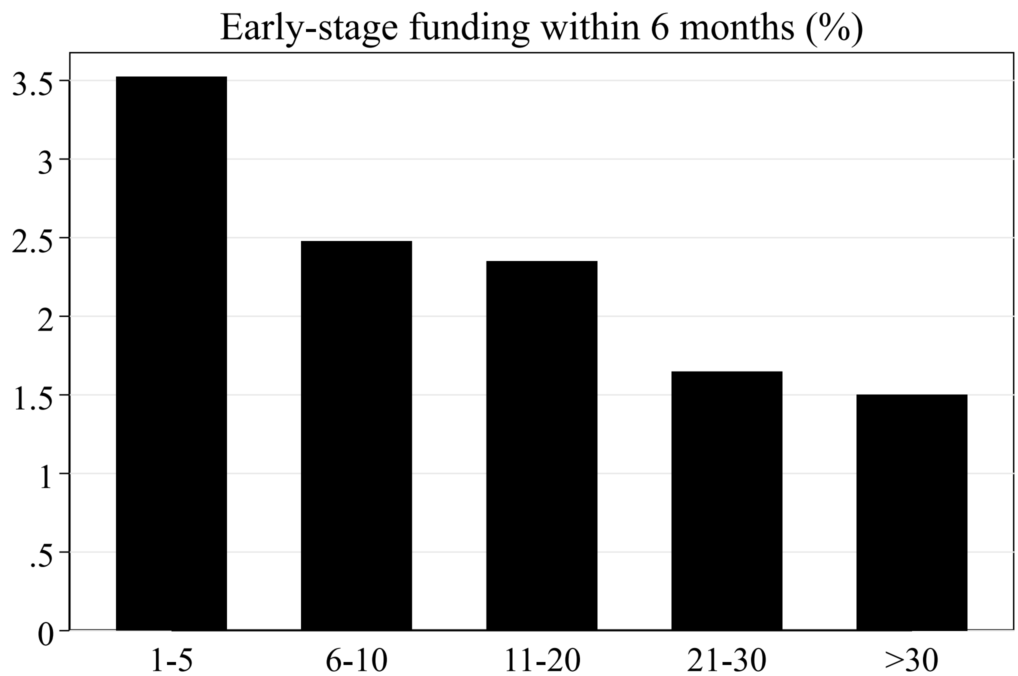
Notes: Figures shows top products in the daily ranking feed of launched and featured products. The three subfigures show, for June 6, 2019, the website ranking feed (where users visit on a computer) and the mobile app ranking feed (specifically, the screenshot is taken with an iPhone device) on that day, as well as the website raning feed in a historical archive (called the "time-travel" section).

Figure 6: End-of-Day Rankings Correlations – Launch Day versus Each Day in First Month After Launch



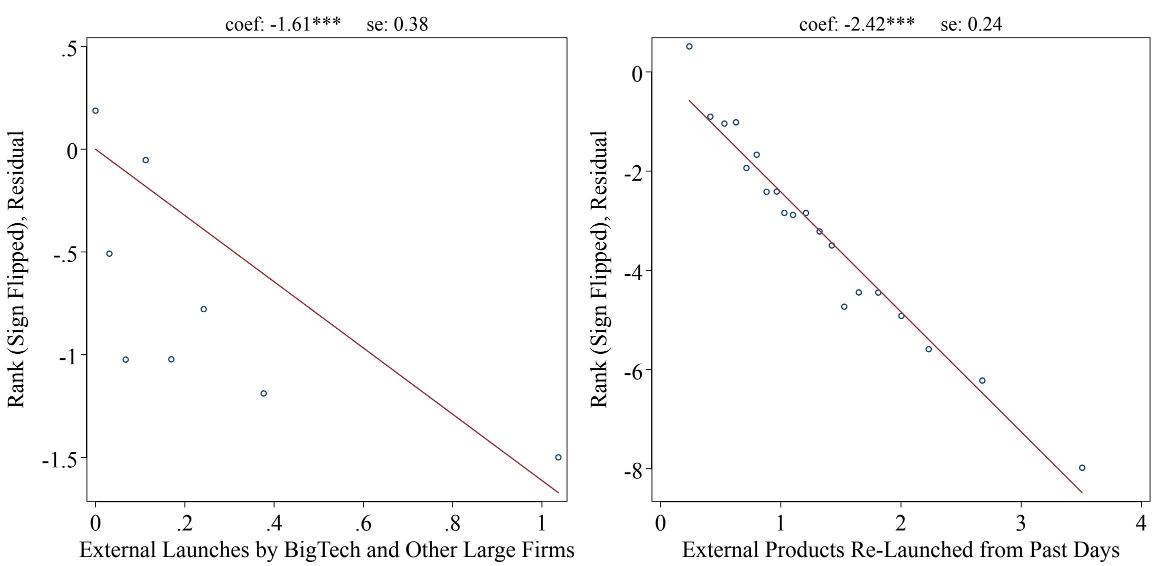
Notes: Figure shows, for all featured products in the sample, the correlations between imputed end-of-launch-day rankings and the imputed end-of-day rankings of the same products on each day of the next month since launch.

Figure 7: OLS Relationship Between Product Rankings and Startup Financing



Notes: Figure shows the average funding probabilities for each product rank bucket 1–5, 6–10, 11–20, 21–30, and below 30, from left to right. The funding outcome is whether the startup launching the product raises seed or early-stage (series A) funding within 6 months of launching on Product Hunt.

Figure 8: First Stage Relationship – Both Instruments



Notes: Figures show the binned scatter plots of the relationships between the instrumental variables and the endogenous regressor – imputed product rankings. The left figure plots the relationship between product rankings and traction-weighted external launches by BigTech and other large companies. The right figure plots the relationship between product rankings and traction-weighted external products that are re-launched on the same day. Regression coefficients and robust standard errors clustered at the launch date level are reported at the top of the graph for each instrument.

Table 1: Distribution of Makers' Geographic Location, 2015 Q2 – 2018 Q1

Product Maker Team Location	N = 22665
North America	54.9%
Canada	5.0%
United States	49.8%
SF Bay Area	9.6%
New York City	5.1%
Boston	0.8%
Europe	30.5%
London	5.0%
Asia (excluding China)	10.3%
Australia	2.6%
Africa	1.0%
Central & South America	0.7%

Notes: Table shows the geographic locations of the majority of maker team members, for technology product launches from the beginning of 2015Q2 to the end of 2018Q1. For product teams that have multiple makers with identifiable locations, the continent of the maker team is the one associated with the largest number of team members, and the region (Canada, USA, and hub regions such as San Francisco Bay Area, New York City, Boston, and London) is tagged if the majority of team members with identifiable locations are located in that region.

Table 2: Sample Descriptive Statistics – Products

	Top Half		Bottom Half	
	N = 12,272		N = 10,847	
	Mean	S.D.	Mean	S.D.
Funding				
CrunchBase Matched	0.37	0.48	0.34	0.47
New Raise in 6 Months (%)				
Seed	2.31	15.01	1.36	11.56
Convertible Note	0.19	4.33	0.18	4.18
Venture Round - Series A	0.46	6.80	0.43	6.57
Latest Raise Prior to Launch (%)				
Seed	9.32	29.08	7.53	26.39
Convertible Note	0.82	9.03	0.61	7.78
Venture Round - Series A	2.42	15.37	1.77	13.19
Product Traction				
Cumulative Upvotes by Launch Day	214.57	181.07	50.87	37.60
Non-FFB Upvotes by Launch Day	201.44	171.72	44.97	29.94
Imputed Launch Day Ranking	6.91	3.68	22.90	7.28
Launch Related				
Re-launch	9.24	63.93	5.42	45.31
Listed Makers	0.87	0.34	0.76	0.42
Media - Images, Videos and Audios	5.40	2.70	5.02	2.87
News Articles Mentions	0.37	1.06	0.21	0.82
Maker Team in VC Hub	0.29	0.45	0.25	0.43
Maker Team in SF Bay Area	0.17	0.38	0.13	0.34
Maker Team Has Female Member	0.19	0.39	0.18	0.38
Hunter Related				
Maker Hunted	0.34	0.47	0.33	0.47
PH Staff Hunted	0.03	0.17	0.03	0.16
Hunter Number of Followers	2409.52	5458.09	1533.87	4024.22

Notes: Table shows descriptive statistics on products in the regression sample. The left panel focuses on products ranked in the top half (1 – 13), and the right panel focuses on products ranked in the bottom half (below 13).

Table 3: Funding Statistics by Post-Launch Months

	Top Half			Bottom Half		
	Seed	Convertible Note	Venture - Series A	Seed	Convertible Note	Venture - Series A
Month						
2	0.73%	0.04%	0.07%	0.25%	0.06%	0.05%
3	1.18%	0.06%	0.13%	0.49%	0.09%	0.12%
4	1.61%	0.12%	0.24%	0.79%	0.11%	0.22%
5	2.04%	0.17%	0.37%	1.09%	0.16%	0.28%
6	2.31%	0.19%	0.46%	1.36%	0.18%	0.43%
7	2.54%	0.24%	0.61%	1.54%	0.20%	0.51%
8	2.87%	0.29%	0.66%	1.74%	0.22%	0.55%
9	3.06%	0.32%	0.82%	1.92%	0.23%	0.68%
10	3.27%	0.34%	0.91%	2.09%	0.26%	0.71%
11	3.43%	0.37%	1.00%	2.21%	0.28%	0.74%
12	3.62%	0.37%	1.06%	2.39%	0.30%	0.84%

Notes: Table shows descriptive statistics on fraction of firms funded (seed, convertible note, and venture round series A) by number of months elapsed since the product launch. The left panel focuses on products ranked in the top half (1 – 13), and the right panel focuses on products ranked in the bottom half (below 13).

Table 4: Selected Parameter Estimates in Product Traction Poisson Model

	Cumulative Upvotes by the End of Launch Day			
	(1)	(2)	(3)	(4)
	2013 - 2014	2015	2016	2017
Featured	0.686***	2.403***	2.784***	2.912***
	(0.046)	(0.028)	(0.025)	(0.025)
Maker Launch	0.901***	0.393***	0.357***	0.346***
	(0.038)	(0.027)	(0.029)	(0.033)
Makers Count	0.019	0.066***	0.081***	0.061***
	(0.019)	(0.007)	(0.005)	(0.005)
Images Count	0.026***	0.018***	0.027***	0.031***
	(0.007)	(0.003)	(0.003)	(0.004)
External Articles	-0.033	0.046*	0.131***	0.106***
	(0.060)	(0.024)	(0.016)	(0.009)
Tagline Words	0.027***	0.016***		0.010
	(0.006)	(0.004)		(0.008)
Description Words		0.003**	0.002**	0.004
		(0.001)	(0.001)	(0.004)
Hunter Followers (Thous.)	0.077***	0.016***	0.021***	0.013***
	(0.009)	(0.003)	(0.002)	(0.002)
Hunter Early Member	0.124***	0.125***	0.261***	0.060
	(0.041)	(0.032)	(0.040)	(0.040)
Launched 12:00 - 12:10 AM	0.554***	0.379***	0.318***	0.228***
	(0.075)	(0.047)	(0.043)	(0.033)
Launched 12:10 - 12:20 AM	0.525***	0.309***	0.219***	0.245***
	(0.104)	(0.058)	(0.053)	(0.047)
Launched 12:20 - 12:30 AM	0.547***	0.369***	0.184***	0.186***
	(0.122)	(0.069)	(0.054)	(0.066)
Launched 12:30 - 12:40 AM	0.543***	0.418***	0.169**	0.137**
	(0.092)	(0.063)	(0.072)	(0.062)
Topic #39: Email	0.633***	0.489***	0.296***	0.179***
	(0.174)	(0.075)	(0.084)	(0.067)
Topic #44: Design Tools	0.607***	0.437***	0.289***	0.273***
	(0.106)	(0.051)	(0.034)	(0.035)
Topic #64: Amazon	1.308***	0.835**	0.339*	0.292**
	(0.420)	(0.329)	(0.185)	(0.119)
Topic #135: Branding	0.649**	0.549***	0.217*	0.204**
	(0.281)	(0.134)	(0.127)	(0.086)
Topic #271: Sketch	0.314*	0.499***	0.172*	0.152**
	(0.161)	(0.145)	(0.103)	(0.078)
No. Obs.	12,235	31,576	39,531	28,882
Pseudo R^2	0.470	0.735	0.732	0.733
Regularization Strength (1se)	0.520	0.919	0.719	1.114

Notes: Table shows a select set of major determinants of end of launch day upvotes and coefficients on these determinants across the training data sets (columns 1 – 4 corresponds to different training data sets split by year of product submission, 2013 late November – 2014, 2015, 2016, and 2017 respectively). Number of observations in the training data sets, as well as pseudo R-squared of the model fit are presented at the bottom of the table. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: First Stage Effects of Instrumental Variables on Product Rankings

	(1)	(2)	(3)	(4)
	BigTech IV		Re-Launch IV	
Traction Weighted External Launches	-1.611*** (0.384)	-1.414*** (0.390)	-2.425*** (0.239)	-2.608*** (0.235)
Year-Quarter FE	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y
Controls	N	Y	N	Y
No. Obs.	23115	23115	23115	23115
R^2	0.232	0.404	0.248	0.424

Notes: Table shows the first-stage relationship between two sets of instruments and imputed product rankings. Number of observations and R-squared are reported at the bottom of the table. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Effects of Product Ranking on Startups' Funding Probability in 6 Months

Panel A: Ex-Post Traction-Weighted Total Launches by Large Firms As IV

	(1)	(2)	(3)	(4)
	OLS	BigTech IV	BigTech IV	BigTech IV
Product Rank	0.118*** (0.012)	0.393** (0.192)	0.399* (0.218)	0.496* (0.277)
Year-Quarter FE	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y
Controls	N	N	Y	Y
Sample Notes				No Event
No. Obs.	23115	23115	23115	22137
First Stage F-Stat		17.559	19.585	19.003

Panel B: Today's Traction-Weighted Total Re-Launched Products As IV

	(1)	(2)	(3)	(4)	(5)
	OLS	Re-Launch IV	Re-Launch IV	Re-Launch IV	Re-Launch IV
Product Rank	0.118*** (0.012)	0.132* (0.072)	0.171** (0.070)	0.175* (0.097)	0.115* (0.065)
Year-Quarter FE	Y	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y	Y
Controls	N	N	Y	Y	Y
Sample Notes				Before 1AM	No Maker
No. Obs.	23115	23115	23115	8824	4193
First Stage F-Stat		102.866	20.785	12.197	49.976

Notes: In this table, each panel shows the effect of a product's launch ranking on the startup's probabilitiy of raising seed and series A funding within the next 6 months. Panel A uses the IV constructed from external product launches by BigTech and other large firms after the current product is already submitted. Panel B uses the IV constructed from all re-launched products that enter today's ranking feed. In both Panel A and B, instruments are constructed by summing up the predicted traction of all the external launches that meet the criteria. All specifications control for launch hour, day of week, and year-quarter fixed effects. In each panel, Column 1 reports baseline OLS results for comparison, column 2 shows the baseline coefficients from the IV estimation, and the rest of the columns control for product and maker characteristics. The controls include hunter variables (follower counts, gender, linked Twitter account, and has non-empty headline), maker variables (makers count fixed effects, location, and gender), and post variables (external articles, default thumbnail, images, videos and audios). Panel A column 4 restricts the sample to launch dates without a major large company event (Apple Special Event, Apple WWDC, Facebook F8, Google Hardware Event, and Google I/O). Panel B column 4 restricts the sample to daily launches no later than 1AM Pacific Time. Panel B column 5 restricts the sample to products that do not list makers and hence initiated by the hunters. Each specification reports robust standard errors clustered at the launch date level. Number of observations and first-stage F-statistics are reported at the bottom of each table. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Differential Effects of Rankings for Products Above and Below Median Rank

	(1)	(2)	(3)	(4)	(5)
	OLS	BigTech IV	BigTech IV	Re-Launch IV	Re-Launch IV
Product Rank x Below 50th %tile	0.092*** (0.017)	0.147 (0.090)	0.132 (0.097)	0.063 (0.053)	0.094* (0.054)
Product Rank x Above 50th %tile	0.117*** (0.032)	0.434** (0.194)	0.406* (0.208)	0.295 (0.202)	0.369** (0.188)
Year-Quarter FE	Y	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y	Y
Controls	N	N	Y	N	Y
No. Obs.	23115	23115	23115	23115	23115
First Stage F-Stats		35.443 44.774	3.415 7.188	60.348 43.636	3.920 6.856

Notes: Table shows differential effects of product rank on subsequent funding probability by rank position. All specifications control for launch hour, day of week, and year-quarter fixed effects. Column 1 presents the OLS regression result for comparison. Columns 3 and 5 control for hunter, maker and post characteristics additionally. All specifications report robust standard errors clustered by launch date. First-stage F-statistics are reported for the interaction between ranking and the product's ranking being below and above median. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Differential Effects by Maker Team's Location

	(1)	(2)	(3)
	OLS	IV	IV
Product Rank	0.090***	0.195**	0.219**
x Not Hub Area	(0.014)	(0.091)	(0.093)
Product Rank	0.136***	-0.076	0.049
x Hub Area	(0.031)	(0.252)	(0.232)
Year-Quarter FE	Y	Y	Y
Day-of-Week FE	Y	Y	Y
Controls	N	N	Y
No. Obs.			
Not Hub Area	13752	13752	13752
Hub Area	5169	5169	5169
First Stage F-Stats			
Not Hub Area		58.882	31.144
Hub Area		24.845	17.294

Notes: Table shows differential effects of product rank on subsequent funding probability by maker team location. All columns regress funding status on the interaction between product rank and whether the maker team is located in a top venture capital destination – San Francisco Bay Area, New York City, London, and Boston. Column 1 presents the OLS regression result for comparison. Column 3 controls for hunter, maker and post characteristics additionally. All specifications control for launch hour, day of week, and year-quarter fixed effects. All specifications report robust standard errors clustered by launch date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Differential Effects by Presence of Female Makers

	(1)	(2)	(3)
	OLS	IV	IV
Product Rank	0.095**	0.458**	0.530**
x Some Female Maker	(0.043)	(0.228)	(0.235)
Product Rank	0.084***	0.089	0.100
x Only Male Makers	(0.014)	(0.096)	(0.095)
Year-Quarter FE	Y	Y	Y
Day-of-Week FE	Y	Y	Y
Controls	N	N	Y
No. Obs.			
Some Female Maker	3434	3434	3434
Only Male Makers	15487	15487	15487
First Stage F-Stats			
Some Female Maker		18.904	4.420
Only Male Makers		66.032	29.420

Notes: Table shows differential effects of product rank on subsequent funding probability by whether there is at least one female maker in the product team. All specifications control for launch hour, day of week, and year-quarter fixed effects. Column 1 presents the OLS regression result for comparison. Column 3 controls for hunter, maker and post characteristics additionally. All specifications report robust standard errors clustered by launch date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

A1 Additional Tables

Table A1: Effects of Product Ranking on End-of-Launch-Day Organic Upvotes

	(1)	(2)	(3)	(4)	(5)
	OLS	BigTech IV	BigTech IV	Re-Launch IV	Re-Launch IV
Product Rank	11.509***	4.106**	2.562	3.594***	4.803***
	(0.217)	(1.772)	(2.014)	(0.580)	(0.539)
Year-Quarter FE	Y	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y	Y
Controls	N	N	Y	N	Y
No. Obs.	23115	23115	23115	23115	23115
First Stage F-Stat		17.559	19.585	102.866	20.785

Notes: Table shows the effect of a product's launch ranking on the cumulative number of organic upvotes obtained by the producta by the end of the launch day. All specifications control for launch hour, day of week, and year-quarter fixed effects. Column 1 presents the OLS regression result for comparison. Columns 3 and 5 control for hunter, maker and post characteristics additionally. All specifications report robust standard errors clustered by launch date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A2: Effects of Product Ranking After Controling for Organic Upvotes

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	BigTech IV	BigTech IV	Re-Launch IV	Re-Launch IV
Organic Upvotes	0.006***	0.001	-0.013	-0.013	0.000	-0.004
	(0.001)	(0.001)	(0.010)	(0.009)	(0.004)	(0.003)
Product Rank		0.101***	0.446*	0.431*	0.131	0.188**
		(0.016)	(0.234)	(0.244)	(0.085)	(0.085)
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y	Y	Y
Controls	N	N	N	Y	N	Y
No. Obs.	23115	23115	23115	23115	23115	23115

Notes: Table shows the effect of a product's launch ranking on the startup's probabilitiy of raising seed and series A funding within the next 6 months, while controling for the number of organic upvotes obtained by the end of the launch date. All specifications control for launch hour, day of week, and year-quarter fixed effects. Column 1 - 2 present the OLS regression results for comparison. Column 1 shows coefficients from running the specification that includes only organic upvotes but not product rank, and column 2 adds product rank to the specification. Columns 3 - 6 present the IV/2SLS regerssion results on product rank, while including organic upvotes as a control variable. Columns 4 and 6 control for hunter, maker and post characteristics additionally. All specifications report robust standard errors clustered by launch date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A3: Relationship Between Traction-Weighted External Launches and Ex-Ante Information

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Hunted by PH Staff or Early Member				Makers Located in VC Hub Region			
	BigTech IV		Re-Launch IV		BigTech IV		Re-Launch IV	
Traction Weighted	-0.005	0.002	-0.001	-0.002	-0.010	-0.006	0.006	0.001
External Launches	(0.008)	(0.007)	(0.004)	(0.004)	(0.010)	(0.010)	(0.006)	(0.005)
Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y	N	Y
No. Obs.	18922	18922	18922	18922	18922	18922	18922	18922

Notes: Table shows, for the set of maker-launched products, the relationship between the instruments and ex-ante variables measuring the product makers' informedness and connection to the Product Hunt internal team. The outcome variables in columns 1 - 4 are whether a product is hunted by a staff member or early user receiving special thanks from Product Hunt; the outcome variables in columns 5 - 8 are whether the maker team primarily reside in a venture capital top destination (San Francisco Bay Area, New York City, London, and Boston). All specifications control for launch hour, day of week, and year-quarter fixed effects. Columns 2, 4, 6, and 8 control for hunter, maker and post characteristics additionally. All specifications report robust standard errors clustered by launch date. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.