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

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Abstract

Recent rise in micro VC and reduction in cost to experimenting with new startup ideas have led to an explosion of startup activity, which makes it harder for venture capital firms to obtain information efficiently in order to carry out due diligence. I explore frictions in VC information acquisition in a unique setting – by using micro data from Product Hunt, a large online platform covering the majority of technology startup launches, I document strong correlations between being featured prominently on Product Hunt and subsequent VC funding. I estimate that an exogenous shift to product ranking that improves the daily rank of an average product by 1 place increases the firm’s chance of obtaining seed funding by 0.7 percentage points in the subsequent 6 months. The effects are twice as large for startups founded by first-time entrepreneurs, and mainly driven by firms in locations where VC money is less accessible. I conclude that frictions in VC information acquisition have real consequences for startup outcomes, and that Product Hunt improves access to venture capital for less advantaged firms and founders.

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1 Introduction

Venture capital facilitates cutting-edge innovations through funding startup companies with the potential to generate lasting impact on market structure and consumer welfare. Today’s most influential public companies such as Apple and Amazon were initially backed by venture capital, whose products and services have revolutionized industry landscape and reshaped consumer habits. VCs provided the necessary funding to bring path-breaking technologies to the market, and contribute to the decisions of entrepreneurial firms through providing guidance in daily operations. A large literature studying innovation and entrepreneurship have established venture capital’s crucial role in fostering the growth and success of early-stage ventures (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).

At the same time, a relatively small number of gatekeepers dominate access to venture capital, which implies that frictions in the process of financing can generate large real effects on outcomes of innovative firms. When a great startup idea faces difficulty in securing funding in an early stage, it may not be able to realize its full potential in the long run. Factors unrelated to firm fundamentals may change venture capital funding decisions and lead to persistent differences in startups’ performance and ultimately their chances of successful exit through IPOs and mergers.

This paper examines frictions in venture capital’s information acquisition. Such frictions, despite being exogenous to firm fundamentals, can cause significant differences in VCs’ funding decisions toward new ventures. The uncertainty and opacity of early-stage ventures imply that information asymmetry between investors and company insiders can potentially render funding outcomes inefficient. The lowering of experimentation costs in recent years have led to an explosion of startup activity, which has made it even harder for VCs to screen deals and perform due diligence. Therefore, seed VCs have found themselves in need of easily digestible signals and readily accessible sources of information to help them evaluate potential funding targets.

Early-stage ventures are particularly hard to evaluate, since they are often pre-revenue or early-revenue, and traditional quantitative valuation methods do not apply. VCs often rely on more ad-hoc approaches such as the step-up method and the risk mitigation method to incorporate and add up multiple pieces of signals, which typically include market fit and customer traction. To explore VC information acquisition and funding decisions, I use micro data from Product Hunt – a large online platform widely used by tech workers, entrepreneurs and investors, which generates
signals on startup product from potential consumers and a community of product enthusiasts. Founded in late 2013, Product Hunt has grown into an online community of over 1 million users from across the world, who submit and discuss latest innovative products from major technology companies and startups. The platform covers the majority of tech startup launches. Larger players like LinkedIn and Microsoft are also active on the platform, whose new products and feature releases often become “hunted” on Product Hunt concurrently with official announcements or coverage of these products and features by major tech news outlets.

Anecdotal evidence suggests that startups treat launching on Product Hunt very seriously. They plan details much in advance for their products to be “hunted”, and prepare for the launch to ensure that they attract as many user upvotes as possible. A successful launch on Product Hunt brings significant benefits to these startups, both improving fundamentals by converting more consumer sign-ups from Product Hunt traffic, and attracting attention from investors who react to the popularity that product seem to have gained through traction among Product Hunt upvoters.

Investors also use Product Hunt to source deals. The recent explosion of startup activities and lowering costs required to test initial ideas and hence lower funding requirement of these early stage businesses has led to more demand for what Product Hunt offers - a centralized and crowdsourced information exchange that generates salient signals about startups that are public and easy to obtain. Such a condensed source of information helps VCs screen startups quickly, and despite the information being potentially noisy, VCs still rely on these signals.

This paper documents that being prominently featured and hitting top ranks on Product Hunt correlates with higher probability of obtaining seed VC funding in the 6 months after the launch, and that conditional on funding status, obtaining higher rank is associated with faster closing of deals, the lead investor being more experienced as measured by number of past deals, and a larger amount of funding.

To estimate the causal impact of product rankings on funding outcomes, I exploit two sources of variation that induce exogenous shifts to product rankings. First, startup firms launching products on Product Hunt cannot anticipate that new products by a major technology company such as Apple and Facebook will be posted on the same day. Major tech firm’s products are almost always highly upvoted and top ranked, which push down rankings of startup products. Major technology companies have no incentive to release products at a strategic time to maximize upvotes from the Product Hunt community. Instead, they are often shared to Product Hunt feed concurrently as a major media outlet such as CNBC covers the product launch. Hence these unexpected high impact

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product posts absorb upvoter attention and push down the rankings of other products.

This more intuitive example motivates another identification approach, which exploits the fact that Product Hunt staff move a varying and non-trivial number of products from previous days into today’s feed in an exogenous manner, which users can neither predict nor respond to. When a larger number of products and higher-traction products are internally moved from previous days into today’s feed, the new products launched today suffer a “crowding out” effect. The number of products moved and their traction among upvoters vary from day to day. I use an intrument calculated as the sum of “predicted” traction of products moved into to today’s feed. “Predicted” traction measures the impact of moved products better than raw counts, since higher impact products will end up with a higher rank and push down a larger number of products’ ranks.

To predict products’ traction (i.e. the total number of upvotes that products get by the end of the day on which they were on the Product Hunt feed to compete with other products for ranking), I train a Poisson model with Lasso regularization on upvotes. The inputs to the model include ex-ante characteristics solely related to the product post and independent from upvoting activity, such as submission time, tagline length, keywords in hunter’s headline, number of descriptive images and videos, etc. The training data contains all products submitted in the previous year. I also include data on “non-featured” products in the training data to come up with more accurate predictions.

In robustness checks, I show that the variation in product ranks induced by these instruments are exogenous to product fundamentals and user activity during the same day. The induced variation in product rank does not correlate with characteristics of the product or firm, but impacts the product’s visibility and status, and hence influences their impression on and amount of attention from investors.

Using these instrumental variable strategies, I estimate that when an average product’s daily rank goes up by 1 place, the firm’s chance of being funded in the next 6 months improves by 0.7 percentage points. This implies that if a product ranked 10th moves up to the 5th place, its chance of obtaining seed funding in the next 6 months increases from a baseline of 6.6% to about 11.9%. The effects are stable across specifications that also control for firm, founder and Product Hunt launch characteristics, and mainly occur for early stage rounds of venture capital – namely, seed, convertible note, and series A.

Lack of ex-ante information about a startup and their founders makes investors more reliant on the crowd signal generated by Product Hunt. By embedding “crowd signal” in a signal acquisition and learning framework, I provide a theoretical model of seed VCs’ decision making process, in
which VCs receive quantifiable signals and update beliefs about the profit potential of an early-stage business based on these signals. In this framework, when VCs face higher prior uncertainty about an early-stage business after aggregating previous signals, the addition of crowdsourced information by Product Hunt ranking impacts investment decision to a greater extent.

Being top ranked particularly helps firms facing greater access barriers to venture capital, implying that Product Hunt potentially alleviates inequality in access to early-stage capital among startups. The effect of product rank is twice as large for startups founded by first-time entrepreneurs as opposed to experienced founders. Being highly ranked is more crucial to securing funding, for founders who have not previously established themselves as successful entrepreneurs. The effects of product ranking are mainly driven by firms located far away from regions where venture capital is most accessible. This includes startups with headquarters outside Silicon Valley, New York City or London, where VC activities are concentrated and most large VC investors are based.

These empirical findings support the theory of differential updating in beliefs about firm potential and hence investment decision based on Product Hunt rankings. More generally, Product Hunt provides an intermediary for start-up founders who otherwise would not be under VC spotlight to provide additional information and signal through letting community members and a larger group of people assess their products. This is especially relevant when the VC investor is on the margin about whether to invest in a firm, after having examined other factors such as having met with the team, in the due diligence period, for example. This is when information generated from platforms such as Product Hunt become valuable providing additional signals that allow the VCs to evaluate the potential of the venture they are considering investing in. When the VCs are on the fence about the decision, such factors may become more crucial than usual.

This paper contributes to three distinct literatures. First, this paper contributes to a large literature on decisions of early-stage VC investors (Shepherd, 1999; Kaplan and Strömberg, 2003; Kaplan et al., 2009; Gompers et al., 2016; Bernstein et al., 2017). In particular, it contributes to academic understanding of the role of information frictions in venture capital decisions, which is particularly important because of large information asymmetry that exists between early-stage investors and company insiders which makes it challenging for investors to predict future revenue of and evaluate the firm’s potential. An experimental or quasi-experimental setting is rare to come by in past literature on this topic, since it is hard to investigate the causal role of information frictions which may correlate with other factors that are hard to separate without running an experiment. Hence the canonical papers on this topic were descriptive (Gompers, 1995). The paper estimates
the causal effect of information frictions by leveraging features of a widely used online platform among VC investors – Product Hunt, which generates sources of exogenous variation in products’ visibility and status, and enables sharp identification of the causal role of information presentation about startup products. It provides concrete empirical evidence that information frictions have real effects on investors’ decisions to finance early stage technology startups.

Second, this paper relates to a literature on leveraging crowd to improve access to entrepreneurial finance. While past literature focuses specifically on crowdfunding (Agrawal et al., 2014; Yu et al., 2017) and found that it democratizes access to capital to underrepresented groups (Mollick, 2013; Mollick and Robb, 2016; Sorenson et al., 2016) and expands 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 new online tools or market can utilize the crowd to open up funding opportunities to founders that are historically excluded from access to venture capital. This paper puts forward a new empirical phenomenon where “crowd” can contribute to new ventures’ access to finance. The paper shows that crowdsourced information on Product Hunt are used by investors as signals to decide whether to make an investment in an early-stage venture, and found that it particularly improves access to VC for underrepresented firms and founders. This is due to the fact that information is less available for underrepresented firms, and that investors are ex-ante less certain about their potential. Product Hunt provides additional information sourced from a crowd of individuals regardless of their locations facilitated by the online platform.

Third, this paper ties into a literature on the impact of online platforms on the real economy. 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, documenting similar designs of online markets in shaping financial investments has been dearth. This paper describes how information aggregation on Product Hunt influences investor behavior, and provides empirical evidence for the causal effect of information frictions from 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).

Finally, this paper introduces a novel data source on products of technology companies that
is potentially useful for future research in entrepreneurship. While past research has relied on historical databases (Baron and Hannan, 2002; Reuters, 2011), Product Hunt aggregates contemporaneous product information that allows studying up-to-date patterns of innovative activities among technology startups.

The remainder of the paper is structured as follows. Section 2 describes Product Hunt data collection and institutional details including the product launching process, and provides descriptive statistics on the sample after combining with company profiles and venture funding data from CrunchBase. Section 3 discusses anecdotal evidence that VCs use Product Hunt to source deals, and illustrates correlations between product ranks and subsequent VC funding. Section 4 explains the source of information friction in product ranks, and provides two identification strategies to causally estimate the effect of exogenous shifts to product rank on VC information acquisition which contributes to observed correlations. Section 5 presents empirical results on the effect of shifting product rank on subsequent chance of obtaining VC funding, and how these effects differ across firm ex-ante characteristics related to access barriers to venture capital funding. Section 6 lays out the theoretical foundation for heterogenous effects of information on Product Hunt, by modeling VCs’ investment particularly as basing decisions on evaluating startups’ revenue potential by adding up signals of quality over time. Section 7 concludes with a discussion around potential areas of future research.

2 Data

This section introduces Product Hunt and its API data on up-to-date tech product launches. I collect detailed micro data on all users, products and upvotes on the platform since Product Hunt was founded until March 2018, by crawling Product Hunt developer API. Additional Product Hunt data on product launches after March 2018 can be obtained similarly for future research and robustness checks. I provide a picture of users that compose the Product Hunt community, and then describes the product launch process. I then explain rules for user upvotes and determination of product ranking after a product goes live. I then describe sample construction, by matching Product Hunt to CrunchBase to get an extended set of firm and founder characteristics as well as venture capital funding data. The rest of the section describes sample summary statistics, and illustrates its representativeness compared to overall startup firms in CrunchBase founded during a similar time period.
2.1 Platform History and Institutional Context

Founded in December 2013 and serving as an aggregator of latest technology products, Product Hunt has now become a major platform for product launches in the tech sector. Major software companies including FAGMA (Facebook, Amazon, Google, Microsoft and Apple) have their latest updates in their product and feature releases announced on Product Hunt as soon as they become official. Contributed by thousands of users, the platform covers the most up-to-date product information in the tech industry. Figure 1 shows a recent product launch that got close to 1,000 upvotes – Amazon Scout, launched on Product Hunt immediately after a CNBC story initially covered the new release by Amazon.

The company itself rose quickly as a successful venture shortly after it was founded in late 2013. TechCrunch awarded Product Hunt “Best New Startup” in 2014. Backed by Y Combinator and having closed series A funding of $6.1 million led by prestigious venture capital firm Andreessen Horowitz in 2014, Product Hunt’s rise to prominence was smooth and also sustained. In December 2016, AngelList acquired Product Hunt for $20 million, further injecting vigor into the platform by merging its investor user base and forming closer connection between startup products and early stage venture investors.

The platform currently has over a million users, about 10% of which are active in the past three months, and over 80 daily product submissions. Figure 2 shows the growth of Product Hunt user base from founding to present. Panel A shows the growth in the total number of users, and Panel B focuses on users who have submitted, upvoted or commented on products in the past 90 days. Both the total number of users and the number of users have steadily increases since December 2013 to present day, while past 90-day active users account for about 10% of all users.

The activities on Product Hunt are powered entirely by community members, who submit the products, upvote them and comment on these products. All community members can participate in upvoting products, while submitting and commenting requires becoming a contributor, which involves a straight-forward process that any user can easily complete within a few days. Being essentially a public, centralized and crowdsourced information exchange on latest products, Product Hunt fills an attention gap by condensing information about most popular start-up firms into a daily list that can be browsed by scrolling down one page. The website is especially compelling for attention deficient individuals, which typically describe busy entrepreneurs and investors in the start-up community, who prefer consuming quick run-down of top products in a condensed list or
daily digest. The platform particularly gives more visibility to more popular products upvoted the most frequently by community members, as product ranking is determined by aggregate community upvotes and contributed by millions of users.

The Product Hunt community consists of entrepreneurs, innovators and investors, and predominantly individuals who work in the tech industry. To get a sense of whom the active contributors to Product Hunt are, I use self-identifying user information from their names and headlines. A majority of active users (71%) of the user profiles are registered using real names, which allows me to identify demographics of these users such as gender. I first use a parser to classify parts of the username into appropriate types, such as “given name”, “surname”, and “corporation name”, and then an online tool “genderize.io” to detect the gender of all the given names. About a quarter of active users of Product Hunt are female.

Over 40% of users have non-empty headlines that describe what they work on and sometimes the organization they are affiliated with, which allows me to infer these users’ occupations. Figure 3 lists the most frequent key phrases (1- and 2-grams) in these headlines ordered by relative frequency. The most common job titles in these headlines include “developer”, “designer”, “founder” and “ceo”, which account for almost 30% of the users who provided a headline. Many roles are related to tech sector and start-up companies (indicated by the prevalence of roles such as “developer”, “software engineer”, “ux”, etc), and a non-trivial fraction are entrepreneurs and senior management roles (indicated by the prevalence of roles such as “founder”, “director”, “ceo”, “manager” etc).

I further summarize the fraction of active 2018 users that are entrepreneurs, senior managers, and investors. I label users as entrepreneurs who have “founder”, “co-founder”, or “entrepreneur” in their headlines, senior managers whose headlines contain keywords such as “CEO”, “director”, “president”, “vice president”, “owner”, “VP”, “COO”, “CFO”, “CMO”, and “CTO”, and investors whose headline contains keywords such as “investor”, “investment”, “venture”, “capital”, and “fund”. The users may have multiple roles – for example, users who are both “founder” and “CEO” of companies are both entrepreneurs and senior managers. By these definitions, about 14% of self-identifying users are entrepreneurs, 14% are in senior management roles, and about 1.5% are investors or work for an investment firm.

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1I perform the standard text processing procedure such as turning all letters to lower case, and removing special characters and common stopwords (e.g. “the”) obtained in dictionary of standard NLP package.
2.2 Product Launch Process

Launching a product on Product Hunt entails a straightforward process. The product is submitted by a “hunter”, who is usually an influencer or one of the product makers. The “hunter” can be any verified “contributors” on Product Hunt, and becoming a contributor involves a close to effortless process accessible for any online user. To launch a product, the “hunter” compiles a list of information, including product name, link to webpage, and product details. Product details include not only descriptive texts, but usually also include images, videos, audios (if posted product is a podcast episode) and book reviews (if posted product is a book). There can be multiple webpage links associated with a product, e.g. different app platforms such as iPhone and Android for the same products, or when a Kickstarter project also has its own separate company website. Some links are to news articles and blog posts that describe the product. The “hunter” can also tag the product with appropriate topics (such as "Productivity", “Health and Fitness”, etc) which identifies category of the product. If members of the product team are registered users on Product Hunt and choose to be identified, they can be tagged as “makers” of the product.

After the product is launched, the “hunters” and “makers” usually kick off a discussion by commenting on the post with further facts about the product, and welcoming community members to engage with the post and provide feedback. Users can give the product an upvote, and comment on the post to interact with other community members also interested in the product. A user can upvote a product only once, and the post remains open for new upvotes and comments as long as the post remains live, even after the day of launching. However, the product has the greatest chance of attracting upvotes on the day of launching. In fact, over 50% upvotes on most products are made within the first 24 hours of product launching. Number of product views and upvotes drop sharply and occur sporadically after the launch day, as the product fades from the daily feed of “popular” or “newest” products.

Among all the products that are submitted on a daily basis, the Product Hunt community team typically selects about a third of the products to put on the front page, which then compete for ranking based on total authentic community upvotes obtained. Being selected to post on the front page is called being “featured” on Product Hunt, and this decision is mainly based on the speed at which the product gains upvotes from users after being launched. However, Product Hunt’s decision

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2 Being a contributor requires having upvoted at least 11 products, having upvoted products for three days consecutively, and having a non-empty headline. These steps can be completed within a few days. A user remains a contributor once s/he becomes one, and no further activity is required for maintaining contributor status. Contributors can submit products and comment on the discussion of product posts, which non-contributors cannot.
takes many factors into consideration, and ultimately determines what becomes “featured” absent any fixed or automatic criterion. The decision to “feature” a product is typically made within a few hours after launching, and it filters the highest quality products with the largest potential for obtaining most upvotes and being popular among Product Hunt users.

Figure 4 provides patterns in daily product submissions over time, for all posts that end up being “featured”. In Panel (A), each bar represents the total number of posts submitted during a given month, between January 2015 and March 2018. The submitted posts are categorized into products, podcast episodes, books and games. It appears that “featuring” podcast episodes, books and games follow a different set of rules than other products, and that during one period of time a large number of posts in these categories are featured at a higher rate relative to other products and that they are systematically different from other products as well. Between October 2014 and January 2017, around 56.6% of all featured content consist of podcast episodes, books and games.

The empirical analysis drops podcast episodes, books and game for obvious reasons. Podcast episodes and books are rarely start-up firms’ major product, but are more like a form of sharing of knowledge and ideas. The company or author associated with games, books and podcasts tend to create a large amount of similar content (e.g. podcasts have many episodes, book authors often write multiple books, and gaming companies tend to release a non-trivial number of games). The mentioning of “featured” products in the rest of the paper always refer to “featured” posts that are not podcast episode, books or games.

Panel (B) of Figure 4 shows monthly share of “featured” posts relative to all products. The share of featured products remains stable over time at around one-third of all product submissions. The initially high share “featured” in the first quarter of year 2015 is due to missing data – Product Hunt drops non-featured content from its API for this period, but all the data from April 2015 onward contains the complete set of product posts regardless of whether they end up being “featured” or not. Panel (D) shows that there is no weekly cyclicity in the share of products that become “featured”. The chance of being “featured” is similar on a Tuesday compared to a Saturday, for example, despite the fact that twice more products are submitted on a typical Tuesday than on a typical Saturday, as shown in strong weekly cyclicity patterns in Panel (C).

On Sep 29, 2015, Product Hunt launched a daily channel for discovering podcast episodes. The number of submitted and featured podcast episodes sharply increased around this time (to be more exact, a short while before the official announcement), and that a large fraction of them are featured. On the front page, these featured podcast episodes are listed alongside other products. Starting Feb 3, 2017, Product Hunt stopped featuring podcast episodes, and largely reined in featuring books and games. A subsequent sharp drop in featured podcast episodes is evidence on exactly the date. The number of books and games submitted do not change much around these platform changes, however, their chance of being featured decrease sharply since the day of the regime change.
Once a product is featured, it competes with other “featured” products on the same day’s front page feed for rank, based on number of authentic user upvotes obtained. Products with the largest number of authentic upvotes rise to the top every day. The rank on the front page depends almost solely on the cumulative number of non-fraudulent Product Hunter user upvotes.\footnote{An upvote can be classified as fraudulent if determined by Product Hunt to be an fake upvote or bot account. However, I do not observe this information which is only internally available to the company.}

Being “featured” gives a product the entry ticket to the front page, an important step for the firm for getting noticed by potential consumers and investors in the community. Upvotes are the emphasis of most firms that launch products on Product Hunt, because it is the channel through which products rise to greater visibility and status. A larger number of authentic upvotes not only increases the product chance of landing a “featured” spot on the front page, but also improves its ranking among other “featured” products on the same day. Higher ranking improves both the likelihood that the product will be seen by a user, and also the potential for being one of the “top ranked products of the day”, a status that firms can directly quote as a signal and impress investors.

2.3 Characteristics of Featured Products

Product Hunt “featured” products are predominantly in the tech sector (about 92% tagged with the topic “Tech”), and users are heavily concentrated in the tech sector as their headlines suggest. Figure 5 shows the most frequent topics associated with launched products, after excluding the “Tech” label. For the most frequent three topics tagged – web apps, iPhone apps, and productivity tools, over 10% of all “featured” products are associated with each of these categories.

Since most upvoting activity and interactions on Product Hunt occur among “featured” products, I provide summary statistics on users who are active “hunters” of featured posts, and also upvoters of these posts, to get a sense of the type of individuals who are active on Product Hunt. Table 1 and 2 present these user summary statistics on “hunters” and upvoters respectively. In Table 1, activities on Product Hunt such as collections and comments made, number of followers, products hunted, made and upvoted all calculated up to the time when the hunter submits a product that becomes featured. There are 27,141 “featured” products between January 2015 and March 2018, and hence the same number of data points in hunter summary statistics. “Hunters” may have submitted more than one product that ended up being “featured”, and hence the data may contain information about the same person but at different points in time. About 30% of “featured” products were submitted by one of the product team members. Only 11% of individuals submitting a “featured” product are female. A substantial fraction of about 12% of these products
“hunted” by employees and early contributors to the Product Hunt community.

Table 2 shows summary statistics on users who have upvoted at least one “featured” product between January 2015 and March 2018. Over half a million unique users have upvoted at least one “featured” product. These statistics that reflect upvoting users’ activities on Product Hunt are the total amount of activity that had occurred by March 31, 2018. These activities including making collections, writing comments, having followers, as well as hunting, making and upvoting products. The typical user, who is likely an upvoter, is much less active on Product Hunt than “hunters” on average, but their upvotes still add up to have large influence on product rankings, given the sheer magnitude of the upvoting user base.

Figure 6 sums up the evolution of number of upvotes on “featured” products. From Panel (A), the distribution of upvotes is drawn spanning every 5 minute bucket of the product launch day. The likelihood of an upvote occurring start at about 20% around midnight, and picks up gradually and peaks at exactly 8AM Pacific Standard Time, before waning for the rest of the day. Panel (B) shows total number of upvotes by day since product launch. The vast majority of upvotes occur on the launch day – when the product lands the front page of the daily feed, where it gets most exposure to the user community and hence the larger number of user views, some of which convert into upvotes.

To augment the set of product characteristics and get a more detailed look into firm characteristics, I link Product Hunt posts with firm data and funding outcomes obtained by scraping CrunchBase API. The linking process and sample construction are described in section 2.4, and extended summary statistics on firms in the final sample for empirical analysis are described in section 2.5.

2.4 Linking to CrunchBase and Sample Construction

To learn about the firms that created the products, I link Product Hunt data to company profiles in CrunchBase. This allows me to obtain more detailed characteristics of product’s firm and its founders. CrunchBase is a comprehensive database covering start-up companies, investors and events assembled from public sources and validated by moderators. The observed information from CrunchBase that relate to the firms include company homepage URL which is used to link to the product webpage of Product Hunt posts, category group, headquarter location, date founded, key employees’ profiles (founders and management teams), as well as funding rounds and investor information.
Linking Product Hunt to CrunchBase entails mapping the URL domain of product link on Product Hunt to company homepage domain in CrunchBase. Start-up firms sometimes change names and website URLs, and these changes are frequently updated in CrunchBase, but Product Hunt post will contain the old URL of the product page. To the extent that historical CrunchBase data snapshots associated with the old homepage URL are available, the rate of match success can be improved. I also obtain firms’ identities of founders and key members of management teams from CrunchBase, and link them to obtain individual characteristics including gender, past entrepreneurial experience and employment history. Variables obtained from CrunchBase through the matching are used as additional control variables to product-level analysis.

I focus the analysis on a sample period from January 1, 2015 to March 31, 2018, and on product-firm pairs for “featured” products that were launched on Product Hunt during this time period. Data pre-2015 were not included in the sample due to the scale of Product Hunt being small within a year of founding, and these data being potentially biased as earliest contributors to Product Hunt tend to be less representative and potentially more biased in taste than the broad base of overall users that registered accounts on the platform at later times throughout the past five years.

On average, among products made by startup companies that launched on Product Hunt, I can match 42.1% of “featured” products in a sample between January 2015 and March 2018. The match rates are stable across months and slowly worsened over time, potentially due to a lag between founding of the company and its being recorded in CrunchBase. Next, I describe the process of handling the raw data that leads to a sample of products and linked firms for regression analysis.

To obtain the sample for the empirical analysis, first, I focus on “featured” product posts that are not podcast episodes, books or games. Then I drop non-product posts such as spam, news articles, infographics, events, surveys and newsletters. I also drop online courses, music and art projects, as well as political organizations and governmental agencies from the sample.

Sometimes the product is hosted on a third party website, such as Github and other online accounts where developers usually host their code and projects, or Shopify, Instagram, Facebook, Twitter etc where vendors manage their online presence. I drop such instances as well. Additionally, a non-trivial portion of product posts are developers’ side projects. These products’ main URL will be the developer’s personal website. I need to drop these posts as well, because these side projects typically have not evolved into start-up companies, otherwise they would have a separate registered
company URL that can be identified, but they had not done this. I drop iPhone and Android apps, browser extensions, WordPress plugins, messenger bots similarly, if they do not have independent company websites other than platforms hosting them.

Sometimes the product post is about a product by a big software firm that has many similar products (and in many cases, these are app developers who launched one of their many apps). In these cases, I also drop the post because I cannot measure other products that are not launched but made by the same company, and how large the share of the launched product is in terms of the profit that it generates to the firm. These include superstar companies whose posts are immediately excluded, such as Google, Microsoft, Apple, Facebook, Amazon, Twitter, and Product Hunt’s own announcement of its new features.

To these products, I find the product URL link and match them to CrunchBase to obtain additional information about startup companies that created these “featured” products. Linking these products to CrunchBase results in over 7,600 matched product-firm pair in my sample, over a time period from January 2015 to March 2018. Figure 7 shows the distribution of firm age at the time of product launch on Product Hunt, calculated as time elapsed from founded date to Product Hunt launch date, for “featured” products in the sample. The majority of launched products within four years of founding, and launches are most likely to happen a year after the firm was founded.

2.5 Sample Summary Statistics

The sample for empirical analysis includes 7,664 featured products launched on Product Hunt between January 2015 and March 2018, each matched to the underlying the startup firm that makes the product and identified in CrunchBase data. Figure 3 splits the sample into two groups – the LHS panel presents statistics on the five most upvoted products by the end of the launch day, and the RHS panel presents statistics on “featured” products that are ranked below the 5th place in total upvotes at the end of the launch day. The daily five most upvoted products are on average 1.6 times more likely to receive early stage VC funding (seed, convertible note, or series A) in the 6 months following the product launch, at 9.8% funding rate compared to 6.1% among firms that are “featured” on Product Hunt but ranked below the 5th.

About 52% of launched firms have headquarters located in the United States, and 16% have headquarters located in Europe. Firms with products ranked top five daily on launch day are more likely to be located in Silicon Valley (17%), compared to other firms with “featured” products (13%). The top ranked firms tend to be younger firms on average, and are more likely to be in
software and IT sectors and less likely to be in financial services and healthcare sectors. The average number of co-founders is about 2. Founders of the firms launching products that become daily top 5 upvoted products are less likely to be first-time founders and less likely to be female.

Some of the differences between statistics shown in the two panels potentially directly result from characteristics of the Product Hunt post and may be unrelated to firm fundamentals. The “hunters” of the 5 daily most upvoted products have almost twice as many followers as average “hunter” of products ranked below the 5th daily, and more descriptive details including images and videos, and cites more external news articles in the post.

2.6 Data Representativeness

To get a sense of the representativeness of the Product Hunt data, in relation to the entire set of startup firms founded around the same time as firms that launch on Product Hunt, I compare the Product Hunt firms with a sample of overall companies founded during a two-year period (2014 – 2015). Since most users and firms that are in the Product Hunt community are based in United States and Europe, I focus on CrunchBase firms with headquarters located in the US or Europe. Figure 8 shows the category group breakdown of the representativeness of firms launching products on Product Hunt, relative to the entire set of firms in CrunchBase.

Panel (A) of Figure 8 focuses on the category group distribution of total firms founded between 2014 and 2015 and based in the US or Europe in the sample, and panel (B) focuses on match rates in these category groups among all CrunchBase firms founded in the same time period in the same locations.

3 Product Rankings and Early Stage VC Funding

This section describes broad correlations between product rankings on Product Hunt and subsequent funding outcomes of startup firms seeking finance at an early stage.

3.1 Anecdotal Evidence on the Product Hunt Effect

Anecdotal evidence suggests that seed VCs seek information from Product Hunt on startups’ products, and use the platform to source deals. Among others, a 2014 Fast Company article states that the surge in number of early-stage startup companies have made investors turn to Product Hunt for gathering information on startup products, as one of the tools to help them “separate the wheat from the chaff”.

Prominent seed fund SV Angel used Product Hunt to source deals, and officially closed deals
with a firm that launched the daily no.2 ranked product TapTalk – a chat app launched on April 11, 2014, according to Pando Daily. Product Hunt is a fast and easy way to see the latest products on the market, and sometimes outpaces even major tech news outlets like HackerNews in releasing information about product launches. Hence investors find Product a convenient tool for collecting startup firms’ product information, especially on firms located outside Silicon Valley and when investors find these firms more opaque and need more information about them.

In December 2016, AngelList acquired Product Hunt for $20 million. The merger of the two companies forms a tighter connection between Product Hunt and the world of early stage venture investors. In fact, several of Product Hunt’s earliest employees and key members of management (e.g. Niv Dror and Erik Torenberg) have gone on to start their own venture capital firms, further bringing value from Product Hunt’s product information and connections formed in the Product Hunt community to translate into insights into venture investments.

Apart from the fact that early stage investors directly look to Product Hunt to quickly obtain more information about startups’ products, being ranked highly on Product Hunt brings more consumers to these startup firms and products as well. Developers and product teams have cited evidence in spikes in visits to homepage and product sign-ups, immediately after the product is launched on Product Hunt and obtained top ranks status after the launch day. The new users brought to these products through the Product Hunt launch and attention from potential customers improves the fundamentals of “featured” firms and their potential future revenue and sales.

Products’ ranking status on Product Hunt impact both VCs’ perception of the firm directly, and also firm fundamentals which indirectly influences the firms’ chance of obtaining funding. The rest of the section shows correlational patterns between product launch rankings and subsequent VC funding details.

Attention from experts also generates more useful discussions to help improve the product. Launching on Product Hunt facilitates an opportunity for start-up founders to solicit feedback from experts on what they have built, what features to add and what things to change about the product, and how to get more customers. It is also a channel for them to engage with users and explain the product in a more personable way. Also benefits (less direct) from the community that’s built by jointly using the website. Sometimes extends to offline. There are meet-ups and events organized via the community that takes place in real life.

In many ways, Product Hunt is a bridge between entrepreneurs who have ideas for a new product and more established individuals in the start-up community such as many community
members of Product Hunt, which would facilitate further connections to investors and increased number of customers. It should be especially important for firms that lack resources or insider connections otherwise. Product Hunt creates a channel for products to gain visibility through a more democratic process which would pick the winner by popularity among community members, which may not otherwise be picked up if the product makers do not have connections to media and investors, or find it difficult to impress key influencers directly.

In addition, Product Hunt also has an encouragement effect on firms that spurs more innovation in the extensive margin. A large number of makers create products solely because Product Hunt exists as a channel that increases the chance that their products will be seen. Product Hunt does not only increase the visibility of existing start-up firms, but also leads to changes in the extensive margin – that more start-up firms are created through the encouragement of knowing of a system through which they may have a chance to succeed.

3.2 Correlations and Patterns in the Data

In the sample constructed as described in Section 2.4, I provide patterns of correlations between early stage funding within 6 months of product launch and product rankings. Product ranks are defined as the relative position of a “feature” product among other products also launched on the same day and show up on the same product feed. Figure 9 shows the average upvotes as well as funding outcome by rank buckets from 1 – 5, 6 – 15, 15 – 30, and below 30. Panel (A) shows that higher ranks are associated with significantly more upvotes on average, and panel (B) shows that higher ranks are associated with larger probability of obtaining early stage funding in the 6 months after the product launch.

Funding chances of products ranked top 5 are particularly boosted, compared to companies with products ranked just below. Firms ranked between the 6th and 15th only receive 70% of the funding that firms obtain with products ranked daily top 5. Figure 10 panel (A) plots the difference in funding status over time, between daily top 5 products and products ranked between 6 and 10 (green line), and between daily top 5 products and products ranked below 10 (maroon line). While firms with higher ranked products have both higher levels of probability of being funded and faster growth trajectory in gaining access to funding, it appears from the graph that being a top 5 product accelerates the growth in funding probability after Product Hunt launch substantially, as reflected in the kink in the green line right at time 0 (indicating product launch event).

Panels (B) - (D) in Figure 10 shows binned scatter plot on the relationship between the log
of product rank and funding characteristics conditional on firm obtaining early stage VC funding within 12 months after launching a product on Product Hunt. These funding characteristics include speed to close deals, lead investors experience measured in total number of past investments, as well as amount of funding. These plots suggest that a higher product rank is associated with significantly deeper lead investors experience, less time leading to deal closing, as well as a larger funding amount. Coefficients of OLS regressions and standard errors are shown at the top of each graph after controlling for weekly cyclicality, year month fixed effects, launch time of day fixed effects (in 10 minute intervals), and whether product is “featured” on the same day of being submitted.

These patterns suggest that product rank obtained on firms’ Product Hunt launches are positively associated with firms’ ability to attract early stage VC funding in the aftermath, and also correlated with more favorable deals conditional on obtaining funding. However, to establish a causal relationship between product rankings and subsequent venture funding requires further analysis beyond these broad correlations and patterns. In the next section, I describe sources of exogenous variation that shifts a product’s ranking without affecting either ex-ante firm fundamentals or user upvotes on the product, which provides identification to the empirical analysis that gets at the causal impact of product rankings.

3.3 Ranking vs. Upvotes

I use ranking as the measure of social information, which also embeds information on upvotes, since ranking is determined by number of upvotes relative to the rest of the products launched and featured on the same day. Presumably both ranking and number of upvotes should consist social information that investors observe. However, as the number and composition of users of Product Hunt changes over time, the (unscaled) number of upvotes on a particular day may reflect many factors specific to the Product Hunt user composition and timing, and does not directly compare with upvotes on a different day a long time apart.

However, looking at rankings allows the investors to directly compare products and firms launched at around the same time, who are thus evaluated by a very similar set of users by launching on the same day. Obtaining a high rank on the daily feed always signals excellent traction with potential consumers and market fit, regardless of the day on which the product is posted. Hence guaranteeing a high rank on the daily feed, whether that means acquiring 1,000 upvotes or 100, is a better measure of “social information” than unscaled number of total upvotes. Another reason
for using ranking rather than raw upvotes is that the ranking is more salient. Top ranked products are much more likely to be noticed by users and attract attention from investors and other experts who may provide feedback to improve the product.

4 Empirical Approach

This section covers the identification strategy for empirical analysis on the Product Hunt product-firm matched sample in detail. First, I describe measurement of product rankings on Product Hunt. Then I discuss the issues around causality identified the effect of product rank on subsequent VC funding of Product Hunt firms.

Section 2 has described how product hunt rankings are generated. The rankings are calculated by total number of present authentic user upvotes (where each upvote weighs equally unless it comes from a bot account or is a spam upvote). The ranking at any time (including after the launch day) accords with all upvotes the product has acquired up to date, including those that it obtained after the end of the launch day. Even though ranking will continue to update based on later upvotes that are made after the launch day, the majority of upvoting happens by the end of the launch day, and hence rankings of featured products are unlikely to change significantly afterwards, and the change occurs very slowly and sporadically but the outcome variable is a short-run funding probability that is at most 6 months post-launch.

Unfortunately, I only observe either the current exact ranking (for products launched on past days, I can only observe updated rank information which incorporates upvotes today), or the historical total upvotes (which would not exclude the spam upvotes or bot accounts – which remains internal information to which I do not have access\textsuperscript{5}). Therefore, I measure the “recovered” rank of the product at the end of the launch day, but counting the total number of user upvotes that the product has obtained by 11:59PM of the launch day and rank all products “featured” on the same day according from top to bottom.

Note that the “recovered” rank contains measurement error due to the spam upvotes which Product Hunt excludes from calculating the rank, but which my “recovered” rank measure does not reflect. Another source of mismeasurement comes from the fact that users are allowed to upvote any time, even after the launch day ended. Almost always, there will be a few products daily whose ranks are flipped after the launched day ended, by users that continued to upvote these products. Unfortunately, I do not observe and cannot retrieve end of launch day actual ranks for all products

\textsuperscript{5}Factors considered to predict spam upvotes include IP address of the registered the account, voting rings, and spikes in upvotes concentrated within a short period of time
launched historically, since ranks of products update to reflect all upvoting activity prior to being currently observed. However, I can retrieve the ranks of recently launched products (for example, less than a few weeks), whose ranks may not differ much from when the launch day ended, and likely to be the ones observed by VCs considering funding the firm.

The following back-of-the-envelope calculation sheds light on the degree to which mis-measuring the rank variable biases the OLS result. Attenuation bias in the OLS estimate should cause the estimate to be biased toward zero, and

\[ \gamma = \frac{1}{1 + \sigma_u^2 / \sigma_x^2} \]

where \( \sigma_x^2 \) is the variance in the regressor, and \( \sigma_u^2 \) is the variance of the measurement error in observed noisy version.

The mis-measured rank can be written as

\[ \tilde{R} = R + u \]

Where \( u \sim N(0, \sigma_u^2) \). However, for most products, I do not observe the actual rank \( R \) at the end of the launch day, since the current ranking always updates to reflect current aggregate upvoting. However, I can get an estimate of the measurement error by looking at a subsample of recently launched products. I scrape the rankings of all “featured” products launched in September 2018. The observed rankings are those reflecting upvotes up to the evening of October 11, 2018 when the scraping code was run. I take these observed rankings to be the true rank \( R \), which is most likely seen when VCs look on Product Hunt to evaluate startups that launched their products in this time period. I then also collect detailed upvote information on all these products, including when these upvotes occurred and hence only accounting for upvotes up to the end of the launch day, to calculate the “recovered” rank which is the noisy regressor \( \tilde{R} \). The I estimate the measurement error as the variance in \( \tilde{R} - R \) – which is about 5.40 among the September 2018 “featured” products. To the extent that this is a typical time period and that the historical mis-measurement error for past products should have similar magnitude, I take this as the estimate of \( \sigma_u^2 \).

The variance of the regressor is about \( \sigma_x^2 = 72.45 \) (this is the square of the Root MSE statistic reported in the main specification). This results in the downward bias \( \gamma = \frac{1}{1 + 5.40/72.45} \approx 0.93 \) from the measurement noise in observed “recovered” product rank.

Apart from the measurement error, it is plausible that the OLS regression is subject to omitted variable bias. The final rank of the product is determined by a combination of factors: users’ upvotes, the day on which it is submitted, and the length of time that Product Hunt allows it to get maximal exposure to user attention (through moving posts’ official launch time). These factors
have a mixture of implications for the direction of bias in the OLS.

First, I explore whether user upvotes indicate quality or noise of the products. Table ?? shows results from OLS regressions of firms’ funding outcomes (the outcome variable used in main specification) on two measures of product traction among Product Hunt upvoters, in the sample of “featured” (and hence ranked) products and a counterfactual sample of “non-featured” products which do not enter the front page for ranking. The regression results suggest that the funding outcome of the “featured” and hence ranked products are significantly positively associated with Product Hunt traction (measured as log number of upvotes). However, among “non-featured” products, the association is weakly negative – that is, for products that do not enter the ranking competition, larger number of upvotes is actually weakly negatively associated with receiving subsequent VC funding.

This contrast suggests that user upvotes are noisy at best, and do not have signal value for the firms’ ability to attract VC funding in the absence of the publicity effect from being “featured” and ranked. The upvotes can even be a negative signal for firms’ ability to attract VC funding, since the coefficients of upvoter traction for the “non-featured” products are negative albeit statistically insignificant. It is quite likely that firms can obtain a few extra upvotes without putting extra effort into the product itself, and without changing firm fundamentals. The firms that are less likely to attract VC funding absent Product Hunt may try harder to gain upvotes in the sense that these upvotes may improve their chance of becoming “featured” and being ranked more highly on Product Hunt, which will result in increased chance of funding.

Additionally, Product Hunt sometimes moves “featured” posts’ official launch time to give some products more exposure on the ranking feed. Such decision to move a post to give it more time is actually associated with a few factors that are correlated with the product’s quality and likelihood to get VC funding. More specifically, moved posts are likely to be less upvoted without Product Hunt’s helping them by giving them extra time; moved posts are also more likely to be submitted at later time of the day, which also may also correlate with unobserved firm characteristics related to its chance with getting VC funding. Table 5 shows coefficients from an OLS regression of whether a post is moved to be given more time on the ranking feed on the predicted traction of the post. Being moved is associated with less traction among upvoters absent the move. Specifics of the “predicted traction” will be discussed in later parts of this section, but it is a measure of the predicted number of launch day upvotes that the product will obtain given only ex-ante post characteristics (and hence agnostic about whether the post was moved, and also about the actual number of launch
day upvotes that the product ended up getting).

On the other hand, actual upvotes of moved posts are on average more than those posts that are not moved, because they have more exposure on the ranking feed and hence more user views, as Table 10 shows. These evidences suggest that the omitted variable in the OLS regression tends to induce downward bias in the effect. Both the presence of noise in measuring ranks and the omission of unobserved endogenous characteristics that determine product ranks lead to underestimated effect size in the OLS regression of product rank on subsequent VC funding.

To recover the causal effect of product rank on subsequent early-stage VC funding outcome, I use an instrumental variable estimation strategy that exploits exogenous variation in the ranking of products. The intuition for constructing such instruments rely on the fact that the timing of particular products’ launches is completely unrelated to the current product’s fundamentals, but they shift down the current product’s ranking exogenously when they happen to be “featured” on the same day and dominate users’ attention. These launches can be used as exogenous shocks to identify the effect of product ranking.

4.1 Product Releases of Large Companies

As Product Hunt is a crowdsourced community of enthusiasts of technology products, users often submit the latest product releases, not only of their own products but also products that are new on the market – which includes those that are prominently reported in the news, which always happens when a large company announces a new product. The large company releases are often “hunted” and shared to Product Hunt concurrently, when media outlets such as CNBC or TechCrunch reports about the new product release. These “hunts” are highly upvoted and obtain top ranking status.

For example, Google Pixel 3 is the latest phone by Google released on October 9, 2018. A TechCrunch article covered the product release with a video introducing features of this latest Google phone, and at the same time, TechRadar surfaced a detailed review on the product specifics – which was immediately “hunted” and posted on Product Hunt’s daily feed of “popular products” at around 9:22AM on the same day. It quickly rose to among the mostly highly ranked products, and was upvoted 340 times by the end of launch day and badged the “no. 2” product of the day. The only product that obtained more upvotes than Google Pixel 3 on the day was a collection of design templates for startup landing pages called Cruip – it was upvoted 800 times and became “no. 1” product of the day.

The exact dates of large companies’ product releases are unanticipated and unpredictable.
Other firms launching products on Product Hunt on a particular day cannot expect that there will be a highly upvoted product release by a large company on the same day, and hence cannot account for this in planning their launch. This worsens the ranking of startup products – if they were launched on a day without clashing with large companies’ highly upvoted products to compete for ranking, their daily rank will be higher.

4.2 Product Hunt Moving Posts to Launch on Later Day

In a similar vein, other sources of exogenous variation can also shift down product ranking. After a product is submitted to the platform, it sometimes gets to have a longer time on the front page, when Product Hunt moves the product to also “feature” on the next day’s front page. Figure 12 panel (A) shows the proportion of “featured” products that lands on the daily launching feed on the same day as they were submitted, a day after they were submitted, or later. About 92% of “featured” products either land on the daily feed of the day on which they are submitted (63%) or the next day (29%), and Product Hunt controls the decision of whether to move a product to be “featured” on a later day.

Two major reasons lead to moving posts. First, when a product is submitted relatively late during the day, it is more likely to be moved to the next day’s feed. In Figure 11, a large fraction of products are submitted in the early morning before 9AM. Since the majority of posts conditional on being “featured”, land on the daily feed the same day when they are submitted, in order to maximize their time and exposure on the daily feed, firms typically get the “hunter” to submit the product in the early morning – this maximizes their chance both of becoming selected by Product Hunt to be “featured”, and of gaining user views of which a certain fraction convert into upvotes. When a product is submitted relatively late, it may not get enough exposure to users since user attention peak in the early morning, and hence Product Hunt may move products that they deem worthy of being “featured” and getting more user attention to be re-launched on the next day, particularly if these products did not get enough attention when they were first submitted due to being late.

Figure 12 panel (B) shows the total number of “featured” products submitted during each hour on an average day, separately for products that land on the daily feed on the same day (green bar), and products that get moved to the next day (maroon bar). An increasing fraction of products over time get moved to the next day. In Product Hunt’s official medium blog, it is stated that most products get featured by 11am daily, and that products submitted after the time will largely not
be featured on the same day.

Products are also more likely to be moved if Product Hunt wants to “feature” them but that the post did not initially attract much user attention. Sometimes the post may need a bit more polishing to appear more compelling to users, or is simply deemed worthy of being “featured” regardless of getting initially relatively smaller number of user upvotes. These posts typically get moved to re-launch on the next day, so that they would get more exposure and publicity, and have already garnered some upvotes when they show up on next day’s feed. Figure 12 panel (C) shows the average number of upvotes obtained in the first hour after a product goes live, by whether the product is “featured” on the same day as submitted, or moved to the next day. The products that get moved to the next day obtain a relatively smaller number of upvotes initially, compared to the products that get “featured” on the same day as submitted. The only exception are those that are submitted at the end of the day, when typically the submit time factor dominates, and that the product is moved to the next day to be given more time on the front page feed, regardless of its initial traction among users.

When a product is live on the feed, users do not observe the time that the product was submitted, but only when approximately the product was posted (by Product Hunt’s official launch time). Users do not observe the reason why Product Hunt moved a particular post either. It is unlikely that they would be able to know ahead of time how many posts and which ones Product Hunt will move from the day before into today’s feed. Also, given that firms on Product Hunt usually plan the launch in advance, and are unlikely to postpone launching due to these subtle factors that are hard for them to pin down or quantify exactly.

Similarly to large firms’ product announcements, these moved posts also shift down rankings of products on the current day’s feed. The products that were moved from yesterday would have already garnered some upvotes from the day before, and start out with a larger number of upvotes when they are re-launched. As a result, they will have a slight advantage over products that are submitted and “featured” on the same day in the competition for ranking. In general, if more posts were moved into today’s feed, the rankings are pushed down for overall products launched on that day, and that when higher traction products are moved (traction has implication for how popular the product will potentially be among upvoters), the average ranking of other products on the daily feed is pushed down even more.
4.3 Identification Strategy using Instrumental Variables

I construct two sets of instruments based on exogenous variations uncorrelated with ex-ante fundamentals that shift down products’ daily ranking. The intuition for the instruments is similar to what motivates motion picture producers when they decide on timing of their movie releases – when there is a blockbuster released around the same time, it tends to have a large impact on box office revenue. Similarly, surprise launches from large firms tend to overshadow a startup’s product and thwart their chances of obtaining top rank status.

To motivate the main instrument, I introduce a simpler and more intuitive instrument first – “surprise launches” from large firms. More specifically, this instrument is calculated as the number of large firm releases that occur after a product is already submitted and on the same day. To characterize large firms, I find all the firms that were founded before 2011 based in the US or in Europe (where the majority of Product Hunt users are) which have launched at least 7 “featured” products between January 2015 and March 2018. The criteria result in 29 companies, including FAGMA (the top technology companies Facebook, Amazon, Google, Microsoft and Apple) and a number of prominent technology companies.\(^6\)

The main instrument used for identification follows the same intuition, but provides a broader range of variation. Constructing the instrument relies upon the fact that Product Hunt moves products from past days into today’s feed, which can be used to identify the degree of exogenous competition that shifts the ranking of current day products. When more posts are moved into today’s feed and when higher “traction” posts are moved, it shifts the rankings of today’s products down even more.

Differentiating post “traction” depends on the observation that some post characteristics are systematically associated with higher likelihood to attract user upvotes. Since users’ actual upvotes on competing products are likely endogenous (e.g. since upvoters on products launched on the same day or consecutive days may share the same user base since there is some continuity in users’ engagement on Product Hunt), I cannot use the actual number of upvotes to measure “traction” of moved posts. Therefore, I construct the “traction” measure as a variable “purged” of endogenous factors associated with actual user upvotes but still able to retain information about the post’s potential attractiveness of upvoters.

\(^6\)The other companies under these criteria are: Linkedin, Dropbox, Twitter, Youtube, Uber, AirBnB, Stripe, Github, Instagram, Spotify, HubSpot, Reddit, Square, Shopify, Buffer, Fitbit, Foursquare, GoPro, GoSquared, IFTTT, Nest Labs, Sticker Mule, Twilio, and Zoho.
To do this, I use a Poisson model to predict the number of upvotes that a product gets at the end of the launch day. Since upvotes on a product is count data (non-negative and discrete), and that end of launch day upvotes on products follow a power-law distribution, the Poisson model is the natural choice for predicting this variable. Inputs to the model include a wide range of post characteristics, including submit time, product characteristics such as topics, hunter’s past activities, headline keywords and gender, etc. The model also takes into account number of total posts submitted on the day. I augment the data size by including also “non-featured” posts into the training data, presuming that characteristics of the post determine the upvotes similarly for “featured” and “non-featured” posts but that being “featured” itself is associated with a significant boost in user views and hence more upvotes. Including the “non-featured” posts triples the size of the training data, and the “featured” status is also an input variable.

Appendix Table A1 lists key determinants (a subset of variables that are picked to have non-zero coefficient by the regularization) of the outcome variable and the associated coefficients, as well as the optimal regularization parameter, from three sets of training data split by year. Column 1, 2, 3, and 4 report coefficients using training data of posts submitted in 2013 – 2014, 2015, 2016, and 2017 respectively. I then use the trained models to predict end of launch day upvotes for all posts submitted in the subsequent year. For example, I use the model trained on 2013 – 2014 data to predict end of launch day upvotes of posts submitted in 2015.

The sum of predicted “traction” of moved posts into a particular day (scaled down by 1,000 for ease of presentation) constitute the instrument for products submitted on that day. Variation in the instrument is at the daily level. The main idea for the instrument is similar to that in Fedyk (2017), which estimates the impact of being presented on the front page on subsequent stock price and trading volume for a subset of Bloomberg news, which are sometimes given a slot on the front page and sometimes not, depending on the volume of “primary important” articles that always get put on the front page which exogenously absorbs available spots for those “secondary important” articles released around the same time. Similarly in the case of Product Hunt, products from past days are exogenously moved into the current day, shifting down ranks of products “featured” on this day, and that higher predicted “traction” of these moved products affect rankings of current day launched products to a larger extent.

To sum up the above in an equation, the main instrument used for identifying the impact of an exogenous shift to product ranking is the weighted sum of moved posts, with weights equal to predicted post “traction” that isolates components about the potential for a post to attract user
upvotes which isolates any endogenous factors.

\[
TractionWeightedMovedPosts_t = \sum_{j \in P_t} \hat{Q}(x^j)
\]  

(1)

Where the instrument for date \( t \) is calculated based on predicted quality \( \hat{Q}(\cdot) \) as a function of characteristics of each product \( j \) submitted before date \( t \) but moved into date \( t \) to be “featured” (i.e. in the set of posts \( P_t \)).

Figure 13 shows the daily variation in this instrument in panel (A), as well as the binned scatter plot of the first stage relationship between the instrument and log product rank. There is a fair amount of variation in the instrument. The first stage strength is sufficiently large to use in an IV/2SLS regression setting, where the F-statistic is much larger than 10.

4.4 Exclusion Restriction

Exclusion restriction for the instruments described in the last section requires that the exogenous shift in ranking be induced by shocks uncorrelated with product launch characteristics and user upvoting toward the launched product. Indeed, this is satisfied for both unanticipated large firms’ product announcements and posts moved by Product Hunt’s internal decision into today’s feed are actions because of the following two reasons. First, the current product’s makers or hunter do not have any control over these events, who are obviously too small to influence either large firms or Product Hunt’s decision regarding other posts. Second, these events occurring cannot possibly depend on the current product’s launch since these are actions made before the current product is submitted, and that what people decided to do in the past cannot be affected by what will happen in the future which is unknown.

One potential caveat to this approach is that the “hunter” may time strategically and avoid days on which many successful products from the day before clutter today’s feed in the early morning. Hence the firms that post on days when a large number of products were moved from the day before may be systematically different. However, this is not very likely since product teams plan the launching of the product ahead of time, and have all the information ready at the planned day of launch including inviting the hunter (who is usually not part of the product team but rather an influencer with large following on Product Hunt) to post on their behalf at the exact time as planned. To further expel the possibility that the instrument drives product firms’ launch timing, I provide a robustness check by restricting the sample to “involuntary launches”, where an external “hunter” submits the product without informing the product team (do not tag the “makers”).
Another potential issue may be that the shifted ranking changes the visibility of the product and hence the number of user upvotes on the product as well. In this case, it would be unclear if any effect that appears to be associated with the product’s rank is actually due to improvement in user upvotes which may directly improve both firm fundamentals post-launch and investors’ perception of the firm’s potential profitability and market demand. Therefore, I include robustness checks that get at measuring the effect of the instrument on actual number of upvotes that the product obtained at the end of the launch day.

Another set of robustness checks relate to ensuring that the instruments are not correlated with firm fundamentals prior to launching its product on Product Hunt. This includes placebo tests where the outcome variable is an ex-ante characteristic, such as funding or founder’s entrepreneurial experience prior to the launch.

5 Results

This section presents results on the effect of product ranking on startup firms’ chance of obtaining early stage VC financing in the subsequent 6 months.

5.1 Main Results

I document that being ranked one place higher on Product Hunt’s daily product feed leads to 0.7 percentage point increase in subsequent probability of obtaining early stage VC funding within 6 months. This effect is evident and strong for firms seeking early stage financing, but not for later stage venture rounds. In all specifications, early stage funding rounds include seed, convertible note, and series A.

Table 6 reports main results on the effects of Product Hunt ranking on early stage startup’s subsequent probability of obtaining early stage funding. A one place higher rank increases the occurrence of financing in seed, convertible note and series A venture round within the next 6 months by 0.6 – 0.7 percentage points for a startup that launches product on Product Hunt. This also implies that if a product ranked 10th moves up to the 5th place, its chance of obtaining seed funding in the next 6 months increases from a baseline of 6.8% to about 11.9%.

The sample includes all Product Hunt firms that can be linked to CrunchBase company profiles, and “featured” between January 2015 and March 2018. This includes 7,664 matched product-firm pairs. Firms in the sample have an average baseline probability of obtaining early stage financing in 6 months of 6.8%. The number of products “featured” on the front page typically ranges between 10 and 40. The median rank of products in the sample is 13.
Table 6 shows main regression results, using traction weighted total posts moved into today as the IV that exogenously shifts a product’s daily rank. All specifications control for year-month fixed effects and weekly cyclicality. The weekly cyclicality is important because there is clear cyclicality in number of products featured on daily feed as well as number of actively upvoting users varying cyclically over a week, as well as firms clearly considering which day during a week strategically to maximize their exposure to upvoters. Year-month fixed effects control for unobserved changes in the Product Hunt platform itself – e.g. number of actively upvoting users as well as types of products that are launched.

OLS results are presented in column 1 for comparison. Column 2 shows results from the baseline specification. Column 3 adds Product Hunt post characteristics as controls. Column 4 controls for firm characteristics, and column 5 controls for founder characteristics additionally. Results are robust to the concern that product makers may decide to pull out of a launch when too many high traction moved products crowd the feed. Column 6 restricts to a subsample of products where maker information is not tagged, indicating “involuntary launch” where the hunter does not notify the product team and hence the latter cannot time the launch strategically. Results are similar to those in columns 2 - 5.

Across all specifications in Table 6, the first stage F-statistics for IV results are sufficiently large to rule out weak instrument. The OLS estimate is biased toward zero, as discussed in section 4, omitted variable bias leads to underestimated effects of product rank in the OLS regression, as upvotes are easier to manipulate than firm fundamentals. To obtain desired funding, firms less able to attract VC funding ex-ante may have a larger incentive to put in additional effort to solicit more upvotes.

Appendix Table A3 shows the absence of a Product Hunt rank effect on venture rounds. Later stage funding is not affected by product ranking on Product Hunt, and the status that firms gain from launching products here benefit them in obtaining initial funding in the very early stage of the firm.

5.2 Effect Heterogeneity and Access to VC

In this subsection, I explore heterogeneous effects of product rank for firms with varying characteristics. Section 6 formalizes the investors’ incentives for incorporating the signal generated from product rankings on Product Hunt into making investment decisions. One major prediction is that investors rely more on product ranking generated on Product Hunt when deciding on firms with
larger ex-ante uncertainty in true underlying productivity. This section explores empirical dimensions of this prediction, and shows that Product Hunt ranking indeed matter more to firms that VCs may have less information about ex-ante.

More specifically, the effect of Product Hunt rank is twice as larger for firms founded by first-time entrepreneurs as opposed to founders who have previously founded other companies. Also, the effects are mainly driven by firms located outside VC hubs where most venture capital activity is concentrated. This includes firms located away from San Francisco Bay Area, New York City, and London – the top three locations where VC firms agglomerate and the majority of venture deals flow into these places.

Table 7 summarizes the sample splits for founder entrepreneurial experience and firm location relative to VC hubs. Each subsample has a sufficiently large number of firms. Firms founded by first-time entrepreneurs are similar in terms of prior funding to firms founded by serial entrepreneurs. However, despite the fact that serial entrepreneur founded firms seem to obtain higher ranking on average, the post-launch funding probability has much improved for first-time founders (at 10%) compared to serial entrepreneurs (at 8.6%). For the sample split on firm headquarter location, firms located in a VC hub is both more likely to have obtained funding before, and more likely to obtain funding in the 6 months after the Product Hunt launch. However, products of firms located in and outside VC hubs seem to have on average similar traction among users.

Table 8 presents the effects for the founder experience sample split. Improving product rank by 1 place is associated with increasing VC funding probability by 8.6-9.5 percentage points among firms founded by first-time entrepreneurs. The size of the effect half as large for firms founded by serial entrepreneurs, and statistically insignificant. This confirms the theory that VC firms may be less certain about the potential of firms founded by entrepreneurs who do not have a track record of starting successful businesses, and hence rely more on Product Hunt product rank to make investing decision on such firms.

One piece of crucial information about the potential of an entrepreneur is past experience – as individuals may believe the performance will mirror track record of the entrepreneur, and infer from their past experience their chance of future success (Gompers et al. (2010), Nanda et al. (2018)). Hence past entrepreneurial experience is a strong signal that opens doors to VC for serial entrepreneur founded firms to potential investors. VCs usually put particularly large emphasis on

7Note the sample size for splitting on founder characteristics is smaller because for founder profiles are observed in CrunchBase for about 80% but not all of the recorded firms in the database, and also a few firms do not report headquarter location.
founder teams in selecting deals. However, when information about founders may be incomplete and there are larger uncertainty around the quality of the founder team, VCs may look to external sources of proof of the startup’s quality, and hence make them rely more on the product rankings generated on Product Hunt.

Another source of difference between investors’ uncertainty toward startup potential comes from distance. Most VCs are located in VC hubs, and it is easier for them to travel to these firms to learn more about the team if the firm is nearby. VCs may find firms located in a faraway location harder to evaluate, and are hence less certain about their potential profitability, and rely on the Product Hunt signal to a larger extent. Table 9 presents the effects for the headquarter location sample split. The effect of product rank is driven entirely by firms headquartered in locations where venture capital is less accessible – that is, outside VC hubs (San Francisco Bay Area, New York City, and London).

Generally, VC firms facing an increasingly large volume of potential deals may find themselves constrained by their limited capacity to evaluate many deals, and hence they rely more on quantifiable measures that are easy to obtain and digest in shaping their decisions to invest in early stage firms. In particular, Product Hunt helps firms with less ex-ante information to a larger extent. These firms face greater access barrier to VC without Product Hunt, which allows them to provide an additional signal about their products to investors. It ameliorates the funding gap that results from firms lacking credentials and may not otherwise be within VCs’ attention span. Through generating a high product signal from Product Hunt, these firms can be given a chance to attract VCs’ attention and given an opportunity to pitch to them.

5.3 Robustness Checks

I rule out alternative mechanisms in which the shift to product rank affects other margins that improve funding probabilities. For example, it may be that being ranked higher makes the product more likely to be clicked on and viewed by users, which directly affect the number of upvotes the product will get, and also change firm fundamentals by increasing potential customer sign-ups. However, this is not the case. Table 10 shows that the exogenous shift to product ranks does not affect the actual number of upvotes that the product will get at the end of the launch day. It appears that the effect on funding is solely driven by rank and not actual upvotes.

Another concern is that the instrument may systematically affect the types and characteristics of products that end up on the product feed. For example, if having more products and higher
traction products moved into today is systematically associated with traction of products currently on the product feed (without moving anything into it yet), then the instrument may be endogenous. However, Table 11 shows that same day launched products’ traction is uncorrelated with the instrument. This means that the products that end up on today’s product feed which are also submitted today do not vary systematically across different values of the instrument, dispelling the endogeneity concern.

Firms’ ex-ante characteristics should also not systematically relate to the instrument. I check this across three dimensions of ex-ante characteristics of the firms which may affect funding outcomes directly. These include whether the firm has obtained early stage VC funding prior to launching on Product Hunt, firm age measured as number of months that elapsed between firm founding and the product launch, and whether the firm is headquartered in a VC hub location. The instrument is uncorrelated with all these characteristics of firms that were determined prior to the product launch. Table 12 shows regression results on these robustness checks.

5.4 Within Founder Effects of Product Hunt

Overall, launching on Product Hunt improves access to early stage capital. By comparing firms founded at different times by the same founder, OLS regression results show that access to the services and benefits from the Product Hunt platform is associated with improved chance of obtaining seed money by 9% within the first two years after the firm was founded.

To examine more broadly the effect of the Product Hunt platform, I compare funding outcomes of firms founded by the same founder, but in time periods when Product Hunt did not exist (founded before 2013) and when it does exist (founded in 2014 or later and launched on Product Hunt within one year of founding). For this exercise, I take all founders of firms in the sample (which have launched products that become featured between January 2015 and March 2018), and collect the founders’ entrepreneurial history from CrunchBase. I run a fixed effects model on founders who have founded a startup between 2010 and 2013, and another startup after 2013 for which a product is launched on Product Hunt.

Table 13 presents the results. The outcome variable is whether the firm managed to raise early stage venture funding (seed, convertible note, or venture round series A) within two years of founding. Column 1 shows that being able to launch on Product Hunt improves funding chance by 9.6%. Column 3 suggests that among funded firms, being able to launch on Product Hunt allows firms to double the amount of money they are able to raise.
However, it may be that the entrepreneurs have learned over time, and hence improved their funding chances in later years compared to early on (2010-2013). To rule out this explanation of the results, I also run a placebo test, keeping the same specification but comparing within the same founder, funding outcomes of a startup they founded between 2010 and 2013 and another startup they founded after 2013 but did not launch a product on Product Hunt. The results are shown in columns 2 and 4. The placebo group seems to experience no different funding outcomes compared to the control group, which is counter evidence to the alternative explanation of entrepreneurial learning.

6 Rationalizing Findings in a Learning Framework

This section lays out a theoretical framework for seed VCs’ evaluation of startup firms and investment decision. In this framework, startup founders and their investors learn about the profitability of the firm gradually, from a series of noisy signals realized over time. My model relates to a model of startup firms learning about their efficiency as they operate in an industry and continue or abandon after realization of signals over time (Jovanovic, 1982).

In this framework, I model startup firms from the angle of seed VC investors, who perceive startup firms to differ in profitability potential, and some constitute higher return or less risky investments than others. The unobserved profit potential is captured by a “quality” parameter $\theta$, initially uncertain and gradually learned over realizations of random Gaussian signals over time. I generalize Jovanovic (1982) in two ways: first, the signals can differ in informativeness (signal distributions have different variances); and second, firms’ heterogeneous baseline observables shape different prior beliefs of investors (statistical discrimination).

In each time periods $0, 1, \ldots, T$, productivity $\eta_t$ is revealed about the startup firm. Higher quality firms with larger $\theta$ will be on average more profitable in each time period through $\eta_t = \theta + \epsilon_t$ where $\epsilon_t$ are firm-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 link function $x_t = \xi(\eta_t)$ at time $t$. The link function is assume known by investors. $\xi(\cdot) \in C_3$ is strictly increasing, continuous and bounded between $\alpha$ and $\bar{\alpha}$ with $\bar{\alpha} > \alpha > 0$. Additionally, assume that $\xi(\cdot)$ is either strictly concave or strictly convex over its entire domain (this implies that $\xi^{(2)}(\eta_t)$ does not intersect 0 anywhere, hence the smoothness condition guarantees that either $\xi^{(2)}(\cdot) > 0$ or $\xi^{(2)}(\cdot) < 0$ on all of its domain).

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

$$\bar{\eta}_T = \left( \sum_{t=0}^T \rho_t \right)^{-1} \sum_{t=0}^T \rho_t \eta_t, \quad \bar{\rho}_T = \sum_{t=0}^T \rho_t$$ (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 $\rho_t$ of signal at time $t$ correspond to the weight placed on signal $\eta_t$ in the mean of the eventual belief $\bar{\eta}_T$.

Most startup firms that launch on Product Hunt to attract investors look for seed money, and may not have generated any sales or demonstrated the ability to be profitable yet. As these entrepreneurs have no proof of revenue, the investors face greater uncertainty in evaluating the startup and hence seed investments are more risky than venture capital. In this model, this means that the baseline certainty $\rho_T$ is smaller, and that an additional signal helps update the investors’ beliefs about the profitability even more. Non-negligible differences in the precision of posterior beliefs among different types of startup firms and entrepreneurs are especially present given limited observables of pre-product firms. There are significant difference among firms evaluated by investors. I formalize this intuition by modeling social information on Product Hunt as a signal of the business’s potential future profitability.

6.1 Updating Beliefs about Profitability on Social Information

Investors use Product Hunt upvotes as a signal of the business’s potential future profitability, when they decide upon potentially investing in an early stage startup. Product launch performance on Product Hunt provide information about product market fit, as higher ranking of the product (resulting from more upvoters) indicate large potential consumer demand. Since the Product Hunt community contains a sample of potential consumers, upvotes of these users suggest consumers’ interest in purchasing the product both inside the sample and in the outside population, and may predict future sales and profit after production.

Before launching products on Product Hunt, startups have different baseline observable characteristics. Investors summarize these characteristics into baseline sufficient statistics $(\bar{\eta}_T, \bar{\sigma}^2_T)$, by aggregating all previous signals based on observables prior to the launch on Product Hunt. Without additional information, $\eta$ is a Gaussian random variable $N(\bar{\eta}_T, \bar{\sigma}^2_T)$. An additional “crowd signal” $\tilde{s}$ is available from the Product Hunt launch and upvotes for startups to be evaluated by investors.
When there is large uncertainty regarding a startup’s potential, investors are likely to update their beliefs about the product’s potential in a significant way based on the “crowd signal” generated based on Product Hunt upvotes, despite such signals being potentially noisy and the generation process of which prone to manipulation.

How the signal is truly generated may be different from the investors’ beliefs. Since upvoters do not necessarily convert to consumers, and upvoting is costless and almost effortless, the crowd signal may be prone to bias and at best a noisy signal of potential consumer demand. I assume agnostic about the true value of the “crowd signal” in that in reality it may not be an unbiased signal of \( \theta \) or need to be correlated with \( \theta \), but investors’ beliefs are that such a signal is an unbiased signal of \( \theta \). Investors may be unaware of or not take the biases in how the signal is generated into account.

\[
\tilde{s} = \theta + \iota
\]  

(3)

Where \( \iota \sim N(0, \sigma^2) \).

Another underlying assumption is that the crowd signal \( \tilde{s} \) is equally informative for startup firms with different baseline characteristics (that is, \( \sigma^2 \) does not vary across product or time period \( T \)). Adding this “crowd signal” to investors’ baseline beliefs lead to updated belief with the below posterior Gaussian distribution for \( \theta \). Denote the precision of each signal as the inverse of the variance, that is \( \rho_T = \tilde{\sigma}^{-2} \) and \( \rho_\iota = \sigma^{-2} \).

\[
\theta(\bar{\eta}_T, \tilde{\sigma}^2_T)|\tilde{s} \sim N \left( (1 - \lambda)\bar{\eta}_T + \lambda\tilde{s}, (\rho_T + \rho_\iota)^{-1} \right)
\]

(4)

Where \( \lambda = \frac{\rho_\iota}{\rho_T + \rho_\iota} \) is the relative precision of the “crowd signal”. It is apparent that \( \lambda \) is the effect of \( \tilde{s} \) on the posterior expected profitability

\[
E \left[ \theta(\bar{\eta}_T, \tilde{\sigma}^2_T)|\tilde{s} \right] = (1 - \lambda)\bar{\eta}_T + \lambda \tilde{s}
\]

(5)

Hence proves the following lemma.

**Lemma 1.** The effect of the crowd signal on investor’s posterior expectation about startup profitability \( E \left[ \theta(\bar{\eta}_T, \tilde{\sigma}^2_T)|\tilde{s} \right] \) is equal to \( \lambda \), the relative informativeness of the “crowd signal”. When the crowd signal is equally informative across firms, i.e. \( \sigma^2 \) is independent of \( (\bar{\eta}_T, \tilde{\sigma}^2_T) \), the effect of crowd signal on investor’s expectation decreases in the variance \( \tilde{\sigma}^2 \) of the prior after aggregating ex-ante information.
More intuitively, $\sigma^2_T$ is a measure of investors’ uncertainty about a startup’s profit potential. Larger uncertainty in the baseline is reflected by larger variance $\sigma^2_T$ after the investor aggregates all signals generated prior to the Product Hunt launch, and means that less is known about future profitability of the startup. As a direct result, investors put more relative weight on the crowd signal exactly when ex-ante uncertainty toward the startup’s profitability is larger.

Such uncertainty have direct empirical equivalents. For example, fewer women founders are in the startup scene, creating a missing data problem where more uncertainty may be involved in evaluating startups founded by women. For founders who have never founded companies before, or who have not obtained funding for their startup prior to launch on Product Hunt, or more generally younger firms, the uncertainty in their potential profitability is larger, and as a result investors should be more reliant on the crowd signal in deciding toward funding these firms.

**Lemma 2.** The gap due to statistical discrimination is the ex-ante difference in means $\bar{\eta}_T - \bar{\eta}'_T$. The extent to which the crowd signal mitigates statistical discrimination is also equal to the relative precision of the crowd signal $\lambda$. This can be written as $E\left[\theta(\bar{\eta}_T, \sigma^2_T) - \theta(\bar{\eta}'_T, \sigma^2_T) | \tilde{s}\right] = 1 - \lambda$. When the crowd signal is extremely precise, $\lambda$ approaches 1 and statistical discrimination is almost completely mitigated as $1 - \lambda = 0$.

Now suppose the true DGP for $\tilde{s}$ is Gaussian $N(\theta_0 + \Delta, \sigma^2_\Delta)$ and $\rho_\Delta = \sigma^{-2}_\Delta$ where $\theta_0$ is the true quality parameter and $\Delta$ is maker generated bias from launching strategically. Then the marginal for the investor’s updated beliefs after seeing the crowd signal, aggregated over the true distribution of $\tilde{s}$ is

$$p\left(\theta^*(\bar{\eta}_T, \sigma^2_T)\right) = \int p\left(\theta(\bar{\eta}_T, \sigma^2_T) | \tilde{s}\right) dp(\tilde{s}) \sim N\left((1 - \lambda)\bar{\eta}_T + \lambda(\theta_0 + \Delta), (\rho_T + \rho_i)^{-1} + \lambda^2 \rho_\Delta^{-1}\right)$$ (6)

### 6.2 Social Information’s Heterogenous Effects on Investment

This part formalizes how investors’ beliefs about startups profitability shape investment decision, and the consequence of updating on the “crowd signal” $\tilde{s}$ for the allocation of seed money toward startups.

 Investors are assumed to be risk-neutral, and face heterogeneous costs to investing in a firm captured by a Gaussian random variable with mean $c$ and variance $\sigma^2_c$. The cost to investing is assumed to be investor specific, and does not vary across startups (so that we completely close the matching channel where some startups and investors are better matches than others and hence have
lower costs when they are matched). The average of the costs of investment is assumed independent of group and hence \( c \) does not vary across firms. Hence the cost can be written as \( c + \epsilon \sigma_c \) where \( \epsilon \sim N(0,1) \) is distributed according to a standard normal variable.

The payoff to investing in a firm is then equal to \( \xi(\theta) - c - \epsilon \sigma_c^2 \). Hence a risk-neutral investor will decide to invest if and only if expected payoff is non-negative. Define the investment decision \( y^* \) as a binary variable of whether the investor decides to invest (i.e. if the expected potential of the startup exceeds the cost of investing).

\[
y^*(\tilde{s}, \epsilon) = \mathbb{1}\left( E\left[ \xi\left( \theta(\tilde{\eta}_T, \tilde{\sigma}_T^2) \right) | \tilde{s} \right] - c - \epsilon \sigma_c \geq 0 \right)
\]  

(7)

For now assume \( \tilde{s} \) and \( \epsilon \) are independently distributed (are there reasons to suppose they are correlated??). Then the expected funding probability is equal to

\[
E \left[ y^* | \tilde{\eta}_T, \tilde{\sigma}_T^2 \right] = P_r \left( \epsilon \leq \frac{1}{\sigma_c} \left[ E\xi \left( (1 - \lambda) \tilde{\eta}_T + \lambda (\theta_0 + \Delta) + \nu \right) - c \right] \right)
\]  

(8)

Where \( \nu \sim N \left( 0, (\rho_T + \rho_s)^{-1} + \lambda^2 \rho_{\Delta}^{-1} \right) = N \left( 0, (\rho_T + \rho_s)^{-2} \left( \rho_T + \rho_s + \rho_T^2 \rho_{\Delta}^{-1} \right) \right) \) and \( \epsilon \sim N(0,1) \). Define \( \rho_* = (\rho_T + \rho_s)^2(\rho_T + \rho_s + \rho_T^2 \rho_{\Delta}^{-1})^{-1} \). Apparently \( \rho_* < \rho_T + \rho_s \) unless the crowd signal is completely precise so that \( \rho_{\Delta} = 0 \) implying equality in the above. We have the below approximation

\[
E \left[ y^* | \tilde{\eta}_T, \tilde{\sigma}_T^2 \right] = P_r \left( \epsilon \leq \frac{1}{\sigma_c} \left[ \xi \left( (1 - \lambda) \tilde{\eta}_T + \lambda (\theta_0 + \Delta) \right) + \frac{\xi^{(2)}}{2 \rho_*^2} \left( (1 - \lambda) \tilde{\eta}_T + \lambda (\theta_0 + \Delta) \right) - c \right] \right)
\]  

(9)

It is reasonable to assume a large \( c \) since startups are high-risk investments and investors are fairly selective about investing in the best ones, and hence it is safe to assume that they only invest in firms that have much better quality than group mean. In fact, we can use funding statistics in the data to calibrate \( c \). If about 9% firms become funded which means that approximately the probability \( P_r(\epsilon \leq 0) \approx 9\% \), this implies that the calibrated \( c \approx 1.3 \sigma_c + \xi(\bar{\eta}^*) + \frac{\xi^{(2)}}{2 \rho_*^2} \bar{\eta}^* \) where \( \bar{\eta}^* = (1 - \lambda) \tilde{\eta}_T + \lambda (\theta_0 + \Delta) \).

Empirically, the average effect of crowd signal \( \tilde{s} \) on the funding probability is derived by taking the comparative static that is the partial derivative of expected funding outcome with respect to \( \Delta \). Denote this quantity by \( EffectSize(\tilde{\eta}_T, \tilde{\sigma}_T^2) \) for a startup with prior information captured by sufficient statistics \((\tilde{\eta}_T, \tilde{\sigma}_T^2)\).

\[
EffectSize(\tilde{\eta}_T, \tilde{\sigma}_T^2) = \frac{\partial E \left[ y^* | \tilde{\eta}_T, \tilde{\sigma}_T^2 \right]}{\partial \Delta}
\]  

(10)
Note that $\Delta$ is partially influenced by the startup firm’s launch strategy, a parameter that causes the crowd generated signal $\tilde{s}$ to deviate from true quality distribution. There is much empirical evidence that launch success (in attracting upvotes that leads to higher ranking) depends on specifics of the launch process, such as time of the day to submit product, number of followers of the hunter (individual who submits the product), media content such as images and videos in the product post, as well as product makers’ efforts to advertise the launch via social media.

Product Hunt would not feature a product unless it already attracted significant attention from community members, and “featuring” serves a screening role to filter out products with low $\tilde{s}$ from being posted to the front page. Therefore, it is reasonable to assume that the crowd signal always improves on the prior, so that $E[\tilde{s}] = \tilde{\eta}^* > \bar{\eta}_T$ always holds for products that becomes “featured”.

$\text{EffectSize}(\bar{\eta}_T, \sigma^2_T)$ can be written as

$$\text{EffectSize}(\bar{\eta}_T, \sigma^2_T) = \frac{\rho_\iota}{\sigma_c} \left[ \frac{\xi^{(1)}(\bar{\eta}^*)}{\rho_T + \rho_\iota} + \frac{\xi^{(3)}(\bar{\eta}^*)}{2(\rho_T + \rho_\iota)\rho_\iota^2} \right] \phi \left( \frac{1}{\sigma_c} \left[ \xi(\bar{\eta}^*) + \frac{\xi^{(2)}(\bar{\eta}^*)}{2\rho_\iota^2} - c \right] \right)$$

(11)

Where $\bar{\eta}^* = \rho_T \bar{\eta}_T + \rho_\iota (\theta_0 + \Delta) / (\rho_T + \rho_\iota)$.

**Theorem 1.** Assume $\theta + \Delta > \bar{\eta}_T$. When $\rho_T$ is sufficiently large, $\text{EffectSize}(\bar{\eta}_T, \sigma^2_T)$ decreases in $\rho_T$. When $\xi(\cdot)$ is the identity function, this holds for all positive values of $\rho_T$.

Detailed proof is in Appendix A1.

### 6.3 Estimating Relative Effect of Social Information

To make statements such as what is the magnitude of change in social information required to shift one unit of investment probability, compared to changing credentials (or baseline characteristics $\bar{\eta}_T$ more generally), it requires calibrating parameters to get at the relative importance of updating on social information. This is captured by comparing the effect size of social information and the effect size of improve prior information $\bar{\eta}_T$. It is immediate that the effect size of social information relative to baseline characteristics is exactly equal to the ratio $\kappa = \rho_\iota / \rho_T$.

To let $\rho_\Delta = \rho_\iota$ and $\xi(\cdot)$ be the identity function and baseline funding probability of 9% yields a relative relationship between effect size and the relative precision ratio of

$$\text{EffectSize}(\bar{\eta}_T, \rho_T) \approx \frac{0.17\kappa}{(1 + \kappa)\sigma_c}$$
6.4 Strategic Launches and Bias in Social Information

While investors may believe the crowd signal is informative (an unbiased albeit with large variance signal of ground truth $\eta$) about the profitability of the investment, it may be that the social proof does not contain any information of value in predicting eventual success of startups. In this case, we should want to understand the realized outcome conditional on investing and the crowd signal.

The upvoters on Product Hunt cannot observe more information about the startup than what is shared publicly. The investors should know more about the startup than an average upvoter on Product Hunt, given they have more communication with the founder than an upvoter does. The investors may differ from the crowd in assessing the startup but they are also more experienced at spotting what is profitable by having done many deals in the past (whereas most Product Hunt upvoters do not have venture investing experience). In this sense the crowd signal is closer to a form of “social proof” than a signal of true value.

Crowd signal is actually depend on the broadly observable characteristics of a startup, as well as the (unobserved) maker’s efforts to increase the upvotes. The upvoters are not all investors and the majority do not end up investing in the firm. They have no more information about the startup than the information that is observable to the investors, while the latter has more experience (than an average Product Hunt upvoter) in evaluating startups. $\Delta$ is the part of upvotes that can be influenced by maker’s effort (through engaging with the community prior to launching, requesting influencers to hunt the product, etc).

More formally, suppose $\Delta = \beta_0 + \beta_1 \bar{\eta}_T + \epsilon_\Delta$. Then we can expect the coefficient $\beta_1$ to be negative. To get at $\beta_1$ we need measures of true quality $\theta_0$ to be able to disentangle from the aggregate observed signal $\bar{s} = \theta_0 + \Delta$. In the empirical section, I use follow-on rounds of funding to distinguish ground truth $\theta_0$.

A potential caveat and alternative mechanism is that if investors show persistent bias against groups with less prior certainty, then it may show up as taste-based discrimination and end up affecting follow-on funding irrespective of true quality. The effect of social information fades over time, and funding trends reverse back to the state of affairs before the launch on Product Hunt.

To address this issue, further data on performance may shed more light. For example, to have sales and revenue, trends of users and download over time will be helpful in getting at arguably more accurate measures of performance than follow-on funding. These will be explored further in my future work. In addition, I must control for observable baseline characteristics to account for
some of the effects of persistent taste-based discrimination.

7 Conclusion
To summarize, the paper shows that an exogenous shift to product rank on Product Hunt “featured” launches improves the chance of startup firm obtaining early stage VC funding in the next 6 months by 0.7 percentage points. The effects are mainly driven by firms with headquarters located outside VC hubs, and the effect sizes are twice as large among first-time founders’ companies. Product Hunt improves access to venture capital for firms and founders who may otherwise lack an opportunity to attract VC attention, 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.

These findings corroborate the anecdotal evidence suggesting that early stage VCs use Product Hunt to source deals, and quantify the effect of improved product ranks on firms’ short-run probability of attracting seed financing. The mechanism through which the effects operate is presentation of product information. When the product is ranked more highly, it is both a signal of popularity that the firm can present to potential investors in pitching, and also more likely to get noticed by being placed in a more visible slot on the daily product feed.

On the other hand, exogenous shifts to product ranking does not affect the eventual number of user upvotes that the product will acquire, and hence such an exogenous shift is unlikely to induce changes in firm fundamentals directly. This rules out the alternative channel where higher rank impact firm fundamentals after the launch which in turn leads to improved funding opportunities. It seems that the more direct impact of being prominently featured on VC attention is the cause for the effects found in this paper.

The paper shows that early stage venture investors react to information generated on Product Hunt, and that exogenous changes in product ranks unrelated to firm fundamentals or traction in terms of user upvotes affect the product’s chance of being funded by VCs after the product launch. It appears that the upvotes generated by user community on Product Hunt is largely noisy and even a negative signal of the firm’s ex-ante ability to attract venture funding. However, the paper remains agnostic about how revenue potential and business aspects of firms correlate with user upvotes and product ranking generated through Product Hunt.

Future work may focus on the long term performance of firms that have launched products on Product Hunt, and examine dimensions of firm performance other than funding. For example, by
incorporating startups’ sales and revenue data into the analysis, the researcher will be able to more accurately measure the “quality” of the crowd-generated signal on Product Hunt, and separate the “value” of crowd upvote from the noise. By linking the data to product adopters and consumer sign-ups, the researcher can gain a more accurate picture of whether Product Hunt launch has a longer term impact on improving firm fundamentals.

Another potential avenue of future research involves examining the divergence between the Product Hunt community of upvoting users and actual consumers that the startup’s product may be targeting. User upvotes may be limited in inferring consumer demand, if the Product Hunt user base composing the set of upvoters for particular products are skewed toward certain tastes that do not reflect the true market that the product fits into.

Additionally, the paper introduces a novel data source on startups’ most up-to-date product offerings, which will potentially be useful for future innovation research involving the product market and consumers served by innovative firms.

References


Thomas J Chemmanur, Karthik Krishnan, and Debarshi K Nandy. How does venture capital


**Figure 1:** Example of Product Launch on Product Hunt: Amazon Scout

Notes: Screenshot shows the Product Hunt page of Amazon Scout, which is Amazon’s latest feature launched on Product Hunt on September 20, 2018.
Figure 2: Product Hunt User Base Growth (2014 – 2018)

(A) All Registered Users

(B) Past 3 Month Active Users

Notes: Figure shows the growth in number of Product Hunt users from January 2014 to March 2018. Panel (A) plots the number of total registered accounts, and panel (B) shows the number of 90-day active user accounts. An account is considered active if the user participated in activities on Product Hunt in the past 90 days including submitting, upvoting, and commenting on products.

Figure 3: Product Hunt Users’ Headline Keywords

Notes: Figure shows the probability distribution of the most frequent (i.e. occurring in more than 1% of all users) 1- and 2-gram keywords associated with users’ headlines. The keywords describe users’ organizational roles and job titles.
**Figure 4**: Temporal Patterns in Product Submissions

(A) Total Featured Posts

(B) Share of Featured Products

(C) Featured Products by Day of Week

(D) Share of Featured Products by Day of Week

**Notes**: Figure shows patterns in products submissions over time between January 2015 and March 2018. Panel (A) focuses on monthly number of post submissions that end up being featured on the front page. Panel (B) plots the monthly share of product submissions that end up being featured. Panel (C) shows weekly cyclicality in number of featured products, and panel (D) shows that there is no weekly cyclicality in the share of products featured among all submitted products. Both panels (C) and (D) plot average values for each day of the week, and +/- one standard deviation from the average in brackets.
**Figure 5:** Share of Products that Tagged Topic

![Graph showing share of products that tagged topic]

**Notes:** Figure shows the distribution of the most frequent topics tagged with a featured product post submitted between January 2015 and March 2018. It shows the fraction of featured products that tag each of the 40 most frequent topics, out of a total of 253 topics defined by Product Hunt.

**Figure 6:** Average Timing of Upvotes on Featured Products

**(A)** Every 5 Minutes on Launch Day

**(B)** Days Elapsed Since Launch Day

![Graph showing average timing of upvotes on featured products]

**Notes:** Figure shows the timing distribution of upvotes on an average featured product. Panel (A) focuses on the number of upvotes in each 5 minute bucket on the launch day. Panel (B) focuses on total number of daily upvotes since the launch day.
Figure 7: Firm Age Distribution at Product Launch

Notes: Figure shows the distribution of firm age at the time of launching product on Product Hunt. The length of time that elapsed since the firm was founded is measured in years on the x-axis. The graph should kernel density estimates of the distribution with optimal bandwidth.
Figure 8: Category Group Representativeness of Regression Sample

(A) Overall Matches in Sample of “Featured” Products

(B) Sample Match Rate of CrunchBase Firms Founded in 2014 – 2015

Notes: Figure shows the sample’s representativeness in all category groups defined in CrunchBase data. The bar graphs focus on all US- and Europe-based firms founded between 2014 and 2015 recorded in CrunchBase. Panel (A) shows the total number of matches in each category group, and panel (B) shows the match rates. Both panels order category groups by the magnitude of the x-axis variable from the highest to the lowest.
Figure 9: Launch Day Upvotes and Subsequent Early Stage VC Funding by Rank Bucket

(A) End of Launch Day Upvotes

(B) Probability of Financing Within 6 Months (%)

Notes: Figure shows average end of launch day upvotes and subsequent VC funding by daily product rank buckets. The buckets are ranks 1–5, 6–15, 15–30, and below 30 from left to right. Panel (A) focuses on number of upvotes at the end of the launch day, and panel (B) focuses on average seed funding rate within 6 months of product launch.
Figure 10: Correlations Between Product Rank and Early Stage VC Funding

(A) Differences in Probability of Being Funded (%)

(B) Outcome: Lead Investor Experience

(C) Outcome: Weeks Until Funding Announced

(D) Outcome: Amount of Funding (Million $)

Notes: Figure shows correlations between trends and characteristics of subsequent early stage VC funding and Product Hunt ranking. Panel (A) plots the average difference in the probability that the venture has obtained early stage funding up to each time period at the weekly level. The green line plots the difference in funding status between firms that hit daily top 5 product rank and firms that enter the product ranking but falls out of daily top 10; the red line plots the difference in funding status between firms that achieved rank from 6 to 10 with their product launch and firms that enter the product ranking but falls out of daily top 10. Panels (2) - (4) show binned scatter plot on the correlations between Product Hunt ranking and funding details among firms that obtained early stage funding in the 12 months after launching on Product Hunt, after controlling for a set of launch timing related fixed effects. Coefficients on the regressions and p-values are shown at the top of each binned scatter plot. Panel (B) focuses on lead investor experience measured by number of past deals. Panel (C) focuses on speed in weeks to announcing the deal. Panel (D) focuses on the amount of funding obtained.
**Figure 11:** Hourly Share of Product Posts Submitted on Average Day

*Notes:* Figure shows the fraction of products submitted during each hour in a day, for all product posts submitted between January 2015 and March 2018.
Figure 12: Characteristics of Moving Posts

(A) Moved Posts Among Featured

(B) Average Featured Posts, by Submit Hour

(C) Average Upvotes on Posts, by Submit Hour

Notes: Figure shows summary graphs of moved posts. Panel (A) shows the distribution in time of delayed launching for all featured posts. Panel (B) and (C) show distribution of the total number and first-hour upvotes of product posts submitted by hour of the day, separately for posts launched on the same day as submitted and for posts that are delayed launching to the next day.
Figure 13: Main Instrument Daily Variation and First Stage

(A) Daily Variation in Main Instrument

(B) Binned Scatter Plot of First Stage in IV/2SLS

Notes: Figure shows summary plots for the main instrument used in the IV/2SLS empirical strategy, quality weighted moved posts. Panel (A) shows the daily variation in the main instrument for all days in the sample (January 2015 – March 2018). Panel (B) shows the binned scatter plot of the first stage relationship between the instrument and the endogenous regressor, log daily rank, along with coefficients and F-statistic presented at the top of the graph.

Table 1: Summary Statistics on Hunters of Featured Products (2015Q1 – 2018Q1)

<table>
<thead>
<tr>
<th>Hunter Characteristics (N = 27141)</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>p90</th>
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<td>Member of Product Team</td>
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Notes: Table shows summary statistics of active 2018 users on the Product Hunt platform.
Table 2: Summary Statistics on Hunters of Featured Products (2015Q1 – 2018Q1)

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Notes: Table shows summary statistics of active 2018 users on the Product Hunt platform.
<table>
<thead>
<tr>
<th></th>
<th>Daily Top 5 (N = 1583)</th>
<th>Other Featured (N = 6081)</th>
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<tr>
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<td>SD</td>
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<td>Seed VC Funding</td>
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<tr>
<td>Within 6 Months (% Yes)</td>
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<td>6.04 23.82</td>
</tr>
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<td>Firm Location</td>
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<td>US</td>
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<td>0.52 0.50</td>
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<td>Europe</td>
<td>0.18 0.38</td>
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<td>0.26 0.44</td>
<td>0.25 0.43</td>
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<td>SF Bay Area</td>
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</tr>
<tr>
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<tr>
<td>Software &amp; IT</td>
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<td>Female</td>
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<td>Launch Day Rank</td>
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<td>19 10</td>
</tr>
<tr>
<td>End of Launch Day Upvotes</td>
<td>360 220</td>
<td>83 67</td>
</tr>
<tr>
<td>Hunter No. Followers</td>
<td>3817 7314</td>
<td>1986 4542</td>
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<td>0.45 1.10</td>
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<tr>
<td>Images and Videos</td>
<td>5.44 2.86</td>
<td>4.46 3.06</td>
</tr>
<tr>
<td>Moved into Today</td>
<td>0.32 0.47</td>
<td>0.25 0.43</td>
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</table>

Notes: Table shows summary statistics on the regression sample of product posts. Variables are categorized into funding related variables, social information, firm characteristics, as well as product post characteristics. The mean, standard deviation and number of observations are reported for each data variable.
### Table 4: OLS Regression of VC Funding on Product Popularity by “Featured” Status

<table>
<thead>
<tr>
<th>Obtained Early-Stage Funding within 6 Months</th>
<th>Featured</th>
<th>(1)</th>
<th>Non-Featured</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.0201***</td>
<td>-0.0033</td>
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<tr>
<td></td>
<td>(0.0030)</td>
<td>(0.0029)</td>
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<td>Log (First Hour Upvotes)</td>
<td>0.0148***</td>
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<tr>
<td></td>
<td>(0.0039)</td>
<td>(0.0040)</td>
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</tr>
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<td>Controls: Weekly Cyclicality</td>
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<td>Fixed Effects</td>
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<td>Year-Month</td>
<td>Year-Month</td>
<td>Year-Month</td>
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<td>Number of Observations</td>
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<td>7750</td>
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<td>Mean Regressor</td>
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<td>1.861</td>
<td>1.388</td>
<td>0.852</td>
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**Notes:** Result table shows the effects of log upvotes on early-stage funding in 6 months after product launch. Columns 1 - 2 show results for “featured” products between January 2015 and March 2018, and columns 3 - 4 show results for “non-featured” products in the same time period, both matched to CrunchBase company profiles. Columns 1 and 3 use log total upvotes by the end of launch day as the regressor or the measure for traction, and columns 2 and 4 use log upvotes obtained in the first hour after the product was submitted as the regressor or the measure for traction. All specifications control for weekly cyclicity and year-month fixed effects. All specifications report robust standard errors clustered at the daily level.
Table 5: Effect of Predicted Traction on Probability of Product Being Moved

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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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</tr>
<tr>
<td>Controls: Weekly Cyclicality</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Firm Characteristics</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Founder Characteristics</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year-Month</td>
<td>Year-Month</td>
<td>Year-Month</td>
</tr>
<tr>
<td>Sample</td>
<td>All</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>7664</td>
<td>7664</td>
<td>7664</td>
</tr>
<tr>
<td>R²</td>
<td>0.107</td>
<td>0.130</td>
<td>0.134</td>
</tr>
<tr>
<td>Fraction Moved</td>
<td>0.265</td>
<td>0.265</td>
<td>0.265</td>
</tr>
<tr>
<td>Mean Predicted Traction</td>
<td>0.143</td>
<td>0.143</td>
<td>0.143</td>
</tr>
</tbody>
</table>

Notes: Result table shows the coefficients from an OLS regression of whether product is moved into today on predicted traction of the product. All specifications control for weekly cyclicality and year-month fixed effects. Column 2 additionally controls for Product Hunt launch characteristics, including the hunter’s influence – number of followers at launch, gender, whether hunter is an entrepreneur, investor, or senior management at startups, whether hunter links Twitter account, and whether hunter has a headline, launch time of day fixed effects in 10 minute buckets, number of external articles linked to the launch, whether product post has a thumbnail picture, and number of image, video and audio content pieces. Column 3 additionally controls for firm characteristics, including CrunchBase classified categories, firm age quarter fixed effects, headquarter location, and previous funding (seed, convertible note and venture) rounds and amount as well as weeks elapsed since last funded. Column 4 additionally controls for characteristics of founding and executive teams, including size, female share, share that had founded companies before, and share that had been employed at “big five” software companies, i.e. Apple, Amazon, Google, Microsoft and Facebook. All specifications report robust standard errors clustered at the daily level.
**Table 6: Effect of Product Rank on Early Stage VC Funding Within 6 Months**

<table>
<thead>
<tr>
<th></th>
<th>OLS (1)</th>
<th>OLS (2)</th>
<th>OLS (3)</th>
<th>OLS (4)</th>
<th>OLS (5)</th>
<th>OLS (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Daily Rank</td>
<td>0.0018***</td>
<td>0.0063*</td>
<td>0.0065**</td>
<td>0.0063**</td>
<td>0.0062**</td>
<td>0.0067**</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0032)</td>
<td>(0.0029)</td>
<td>(0.0028)</td>
<td>(0.0028)</td>
<td>(0.0029)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>IV/2SLS (1)</th>
<th>IV/2SLS (2)</th>
<th>IV/2SLS (3)</th>
<th>IV/2SLS (4)</th>
<th>IV/2SLS (5)</th>
<th>IV/2SLS (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Daily Rank</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**First Stage Dependent Variable: Product Daily Rank**

<table>
<thead>
<tr>
<th>Traction Weighted Moved Posts</th>
<th>-1.7877***</th>
<th>-1.9809***</th>
<th>-2.0107***</th>
<th>-1.9952***</th>
<th>-3.8471***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.2784)</td>
<td>(0.2553)</td>
<td>(0.2543)</td>
<td>(0.2566)</td>
<td>(0.6660)</td>
</tr>
</tbody>
</table>

**Controls:**
- Weekly Cyclicality: Y
- Post Characteristics: N
- Firm Characteristics: N
- Founder Characteristics: N

**Fixed Effects:**
- Year-Month
- Year-Month
- Year-Month
- Year-Month
- Year-Month
- Year-Month

**Sample:**
- All
- All
- All
- All
- All
- No Maker Tagged

**Number of Observations:**
- 7664
- 7664
- 7664
- 7664
- 7664
- 1619

**Mean Outcome:**
- 0.068
- 0.068
- 0.068
- 0.068
- 0.068
- 0.042

**Median Rank:**
- 13
- 13
- 13
- 13
- 13
- 22

**R²:**
- 0.033
- 0.003
- 0.008
- 0.065
- 0.083
- 0.193

**First Stage F-Statistic:**
- 94.252
- 79.340
- 20.265
- 19.351
- 6.017

**Notes:** Result table shows the effects of Product Hunt daily ranking on early-stage funding in 6 months after product launch. All specifications control for weekly cyclicality and year-month fixed effects. Column 2 additionally controls for firm characteristics, including CrunchBase classified categories, firm age quarter fixed effects, headquarter location, and previous funding (seed, convertible note and venture) rounds and amount as well as weeks elapsed since last funded. Column 2 also controls for characteristics of founding and executive teams, including size, female share, share that had founded companies before, and share that had been employed at “big five” software companies, i.e. Apple, Amazon, Google, Microsoft and Facebook. Column 3 additionally controls for Product Hunt launch characteristics, including the hunter’s influence – number of followers at launch, gender, whether hunter is an entrepreneur, investor, or senior management at startups, whether hunter links Twitter account, and whether hunter has a headline, launch time of day fixed effects in 10 minute buckets, number of external articles linked to the launch, whether product post has a thumbnail picture, and number of image, video and audio content pieces. Column 4 adds a more stringent time fixed effects control at the year-month level. Column 5 focuses on products that are launched yesterday before the daily feed upvote competition begins, and moved to be featured today. Column 6 focuses on product posts submitted by an external “hunter”, who is not a member of the product maker team. All specifications report robust standard errors. OLS estimates and first stage results and F-statistics are reported alongside the IV estimates in each column.
Table 7: Summary Statistics on Effect Heterogeneity Subsamples

<table>
<thead>
<tr>
<th></th>
<th>Funded In 6 Mo</th>
<th>Median Rank</th>
<th>St Dev Rank</th>
<th>No. Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Firm ( N = 7629 )</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not in VC Hub</td>
<td>5.8%</td>
<td>13</td>
<td>11.1</td>
<td>5745</td>
</tr>
<tr>
<td>In VC Hub</td>
<td>10.0%</td>
<td>13</td>
<td>11.0</td>
<td>1884</td>
</tr>
<tr>
<td><strong>Founder ( N = 4885 )</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not Serial Entrepreneur</td>
<td>10.0%</td>
<td>13</td>
<td>10.9</td>
<td>3281</td>
</tr>
<tr>
<td>Serial Entrepreneur</td>
<td>8.6%</td>
<td>11</td>
<td>10.4</td>
<td>1604</td>
</tr>
</tbody>
</table>

Notes: Summary table shows the proportion of firms that are in each sample split, and the baseline average funding rates in each split. The top row in each split describes the subsample where ex-ante uncertainty is relatively higher, and the bottom row in each split describes the subsample where ex-ante uncertainty is relatively lower.

Table 8: Heterogeneous Effects of Product Rank by Founder Experience

<table>
<thead>
<tr>
<th></th>
<th>Obtained Early-Stage Funding within 6 Months</th>
<th>OLS (1)</th>
<th>IV/2SLS : Main Instrument (2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Not Serial Entrepreneur</strong></td>
<td>0.0023*** (0.0005)</td>
<td>0.0086* (0.0049)</td>
<td>0.0095** (0.0044)</td>
<td></td>
</tr>
<tr>
<td><strong>Serial Entrepreneur</strong></td>
<td>0.0016*** (0.0006)</td>
<td>0.0052 (0.0071)</td>
<td>0.0046 (0.0072)</td>
<td></td>
</tr>
<tr>
<td>Controls: Weekly Cyclicality</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Controls: Post Characteristics</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Controls: Firm &amp; Founder Characteristics</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year-Month</td>
<td>Year-Month</td>
<td>Year-Month</td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>4909</td>
<td>4909</td>
<td>4909</td>
<td></td>
</tr>
<tr>
<td>Mean Outcome</td>
<td>0.095</td>
<td>0.095</td>
<td>0.095</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.033</td>
<td>-0.004</td>
<td>0.088</td>
<td></td>
</tr>
<tr>
<td>First Stage F-Statistic</td>
<td>8.768</td>
<td>6.598</td>
<td>4.208</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Table shows regression results on heterogeneous effects of social information on subsequent funding probability. First row shows effects on firms with larger ex-ante uncertainty and less prior information, and the second row shows effects on firms with smaller ex-ante uncertainty and more prior information. Columns 1 and 3 run the baseline specification, which controls for year-month fixed effects and weekly cyclicity. Columns 2 and 4 additionally controls for firm age and category groups.
Table 9: Heterogeneous Effects of Product Rank by Firm Headquarter Location

<table>
<thead>
<tr>
<th></th>
<th>Obtained Early-Stage Funding within 6 Months</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS (1)</td>
<td>IV/2SLS : Main Instrument (2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Not in a VC Hub</td>
<td>0.0018*** (0.0003)</td>
<td>0.0066* (0.0034)</td>
<td>0.0072** (0.0031)</td>
</tr>
<tr>
<td>In a VC Hub</td>
<td>0.0017** (0.0007)</td>
<td>0.0016 (0.0073)</td>
<td>-0.0001 (0.0075)</td>
</tr>
<tr>
<td>Controls: Weekly Cyclicality</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Post Characteristics</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Firm &amp; Founder Characteristics</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Number of Observations 7661</td>
<td>Mean Outcome 0.068</td>
<td>R² 0.032</td>
</tr>
<tr>
<td></td>
<td>First Stage F-Statistic 12.564</td>
<td>7.833</td>
<td>4.754</td>
</tr>
</tbody>
</table>

Notes: Table shows regression results on heterogeneous effects of social information on subsequent funding probability. First row shows effects on firms with larger ex-ante uncertainty and less prior information, and the second row shows effects on firms with smaller ex-ante uncertainty and more prior information. Columns 1 and 3 run the baseline specification, which controls for year-month fixed effects and weekly cyclicality. Columns 2 and 4 additionally controls for firm age and category groups.
### Table 10: Relationship Between Instrument and Launch Day Upvotes

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Is Moved</strong></td>
<td>37.819***</td>
<td>39.178***</td>
<td>41.131***</td>
<td>41.514***</td>
</tr>
<tr>
<td></td>
<td>(5.530)</td>
<td>(5.355)</td>
<td>(5.346)</td>
<td>(5.291)</td>
</tr>
<tr>
<td><strong>Traction Weighted Moved Posts</strong></td>
<td>2.813</td>
<td>-0.887</td>
<td>-1.576</td>
<td>-1.423</td>
</tr>
<tr>
<td></td>
<td>(3.284)</td>
<td>(3.108)</td>
<td>(3.032)</td>
<td>(3.047)</td>
</tr>
<tr>
<td>Controls: Weekly Cyclicality</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Post Characteristics</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Firm Characteristics</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Founder Characteristics</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year-Month</td>
<td>Year-Month</td>
<td>Year-Month</td>
<td>Year-Month</td>
</tr>
<tr>
<td>Sample</td>
<td>All</td>
<td>All</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>7664</td>
<td>7664</td>
<td>7664</td>
<td>7664</td>
</tr>
<tr>
<td>R^2</td>
<td>0.156</td>
<td>0.240</td>
<td>0.272</td>
<td>0.280</td>
</tr>
<tr>
<td>Average Upvotes</td>
<td>140.011</td>
<td>140.011</td>
<td>140.011</td>
<td>140.011</td>
</tr>
<tr>
<td>Fraction Moved</td>
<td>0.265</td>
<td>0.265</td>
<td>0.265</td>
<td>0.265</td>
</tr>
<tr>
<td>Average Instrument</td>
<td>1.156</td>
<td>1.156</td>
<td>1.156</td>
<td>1.156</td>
</tr>
<tr>
<td>SD Instrument</td>
<td>0.864</td>
<td>0.864</td>
<td>0.864</td>
<td>0.864</td>
</tr>
</tbody>
</table>

**Notes:** Result table shows the coefficients from an OLS regression of end-of-launch-day upvotes on total traction-weighted posts moved into the day. All specifications control for weekly cyclicality and year-month fixed effects. Column 2 additionally controls for Product Hunt launch characteristics, including the hunter’s influence - number of followers at launch, gender, whether hunter is an entrepreneur, investor, or senior management at startups, whether hunter links Twitter account, and whether hunter has a headline, launch time of day fixed effects in 10 minute buckets, number of external articles linked to the launch, whether product post has a thumbnail picture, and number of image, video and audio content pieces. Column 3 additionally controls for firm characteristics, including CrunchBase classified categories, firm age quarter fixed effects, headquarter location, and previous funding (seed, convertible note and venture) rounds and amount as weeks elapsed since last funded. Column 4 additionally controls for characteristics of founding and executive teams, including size, female share, share that had founded companies before, and share that had been employed at “big five” software companies, i.e. Apple, Amazon, Google, Microsoft and Facebook. All specifications report robust standard errors clustered at the daily level.
Table 11: Relationship Between Instrument and Predicted Upvotes

<table>
<thead>
<tr>
<th>Predicted Launch Day End Upvotes</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traction Weighted Moved Posts</td>
<td>5.075</td>
<td>4.318</td>
<td>4.223</td>
<td>4.390</td>
</tr>
<tr>
<td></td>
<td>(3.293)</td>
<td>(3.316)</td>
<td>(3.384)</td>
<td>(3.375)</td>
</tr>
<tr>
<td>Controls: Weekly Cyclicality</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Post Characteristics</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Firm Characteristics</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Founder Characteristics</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year-Month</td>
<td>Year-Month</td>
<td>Year-Month</td>
<td>Year-Month</td>
</tr>
<tr>
<td>Sample</td>
<td>Not Moved</td>
<td>Not Moved</td>
<td>Not Moved</td>
<td>Not Moved</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>5633</td>
<td>5633</td>
<td>5633</td>
<td>5633</td>
</tr>
<tr>
<td>R²</td>
<td>0.202</td>
<td>0.373</td>
<td>0.394</td>
<td>0.398</td>
</tr>
<tr>
<td>Average Predicted Upvotes</td>
<td>145.651</td>
<td>145.651</td>
<td>145.651</td>
<td>145.651</td>
</tr>
<tr>
<td>Average Instrument</td>
<td>1.058</td>
<td>1.058</td>
<td>1.058</td>
<td>1.058</td>
</tr>
<tr>
<td>SD Instrument</td>
<td>0.831</td>
<td>0.831</td>
<td>0.831</td>
<td>0.831</td>
</tr>
</tbody>
</table>

Notes: Result table shows the coefficients from an OLS regression of predicted end-of-launch-day upvotes on total traction-weighted posts moved into the day, for products that were submitted and launched on the same day. All specifications control for weekly cyclicality and year-month fixed effects. Column 2 additionally controls for Product Hunt launch characteristics, including the hunter’s influence – number of followers at launch, gender, whether hunter is an entrepreneur, investor, or senior management at startups, whether hunter links Twitter account, and whether hunter has a headline, launch time of day fixed effects in 10 minute buckets, number of external articles linked to the launch, whether product post has a thumbnail picture, and number of image, video and audio content pieces. Column 3 additionally controls for firm characteristics, including CrunchBase classified categories, firm age quarter fixed effects, headquarter location, and previous funding (seed, convertible note and venture) rounds and amount as well as weeks elapsed since last funded. Column 4 additionally controls for characteristics of founding and executive teams, including size, female share, share that had founded companies before, and share that had been employed at “big five” software companies, i.e. Apple, Amazon, Google, Microsoft and Facebook. All specifications report robust standard errors clustered at the daily level.
Table 12: Relationship Between Instrument and Ex-Ante Firm Characteristics

<table>
<thead>
<tr>
<th>Characteristics of Startup Company Prior to Product Hunt Launch</th>
<th>Previously Backed by Early Stage VC (1)</th>
<th>Firm Age ( # Months ) (2)</th>
<th>Headquarter in a VC Hub (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is Moved</td>
<td>-0.030**</td>
<td>-1.828</td>
<td>-0.938</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(1.218)</td>
<td>(1.154)</td>
</tr>
<tr>
<td>Traction Weighted Moved Posts</td>
<td>0.000</td>
<td>0.295</td>
<td>0.342</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.860)</td>
<td>(0.838)</td>
</tr>
<tr>
<td>Controls: Weekly Cyclicality</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Post Characteristics</td>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Controls: Firm Characteristics</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Controls: Founder Characteristics</td>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year-Month</td>
<td>Year-Month</td>
<td>Year-Month</td>
</tr>
<tr>
<td>Sample</td>
<td>All</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>7664</td>
<td>6407</td>
<td>7661</td>
</tr>
<tr>
<td>R²</td>
<td>0.043</td>
<td>0.017</td>
<td>0.016</td>
</tr>
<tr>
<td>Average Outcome Variable</td>
<td>0.328</td>
<td>32.344</td>
<td>0.247</td>
</tr>
<tr>
<td>Fraction Moved</td>
<td>0.265</td>
<td>0.270</td>
<td>0.265</td>
</tr>
<tr>
<td>Average Instrument</td>
<td>1.156</td>
<td>1.216</td>
<td>1.156</td>
</tr>
<tr>
<td>SD Instrument</td>
<td>0.864</td>
<td>0.858</td>
<td>0.864</td>
</tr>
</tbody>
</table>

Notes: Result table shows the coefficients from OLS regressions of ex-ante firm characteristics on total traction-weighted posts moved into the day. All specifications control for weekly cyclicality and year-month fixed effects. Column 2, 4, and 6 additionally controls for Product Hunt launch characteristics, as well as firm and founder characteristics that are orthogonal to the outcome variables. Columns 1 - 2 focus on whether the startup firm has obtained early stage rounds of VC funding prior to the product launch. Columns 3 - 4 focus on firm age measured in number of months elapsed since firm was founded until it launched the product on Product Hunt. Columns 5 - 6 focus on firm headquarter location, and more specifically whether firm headquarter is located in a VC hub (San Francisco Bay Area, New York City, or London). All specifications report robust standard errors clustered at the daily level.

Table 13: Product Hunt’s Effect on Seed Investment within 2 Years of Founding

<table>
<thead>
<tr>
<th>Funding Probability (%)</th>
<th>Log (Funding Amount) x 100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
<td>Placebo</td>
</tr>
<tr>
<td>Founded After 2014</td>
<td>9.60***</td>
</tr>
<tr>
<td></td>
<td>(3.39)</td>
</tr>
<tr>
<td>Fixed Effects: Founder</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Firm Category + Location</td>
<td>Y</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1085</td>
</tr>
<tr>
<td>Number of Unique Founders</td>
<td>501</td>
</tr>
<tr>
<td>R²</td>
<td>0.60</td>
</tr>
<tr>
<td>Mean Outcome</td>
<td>38.06</td>
</tr>
<tr>
<td>Mean Regressor</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Notes: Table shows the effects of the existence of the Product Hunt platform on firms’ access to seed funding, controlling for within-founder fixed effects. Columns 1 and 3 shows the coefficients for treatment relative to the control group. Columns 2 and 4 shows the coefficients for placebo relative to the control group. Treatment group is defined by firms founded after 2014 and have launched a product on Product Hunt within 1 year of founding. Placebo group is defined by firms founded after 2014 and have not launched a product on Product Hunt within 1 year of founding. Control group is defined by firms founded between 2010 and 2013, and could not have launched a product on Product Hunt within 1 year of founding, since Product Hunt did not exist until December 2013.
A1 Proof of Theorem

Lemma 3. When $\rho_T$ and $\rho_i$ are well-defined (that is, strictly positive since they are the inverse of strictly positive and non-degenerate variances) and $\xi(\cdot) \in C^4$ bounded, strictly positive, strictly increasing and either strictly concave or strictly convex over its entire domain, it follows that $\xi^{(k)}(\eta^*)$ is well-defined and bounded for all $k \leq 4$, and $\xi^{(k)}(\eta^*)$ is strictly positive for each $k \in \{0, 1\}$, and $\xi^{(2)}(\eta^*)$ is either strictly positive or strictly negative.

Proof. Since $\eta^* = (1 - \lambda)\eta_T + \lambda s^*$ for some fixed $s^*$ where $\lambda = \frac{\rho_T}{\rho_T + \rho_i}$, it is bounded between $\eta_T$ and $s^*$. Hence $\xi^{(k)}(\eta^*)$ is defined for all $k \leq 3$ since $\xi(\cdot) \in C^4$ and bounded since $\eta^*$ takes values in a closed interval.

By assumption, $\xi(\cdot)$ is strictly increasing, and $s^* > \eta_T$. Hence $\xi^{(0)}(\eta^*) \in [\xi(\eta_T), \xi(s^*)]$. Denote $\alpha_0 = \xi(\eta_T)$ and $\bar{\alpha}_0 = \xi(s^*)$. Since $\xi(\cdot)$ is strictly positive, we have $\bar{\alpha}_0 > \alpha_0 > 0$.

Since $\xi(\cdot)$ is strictly increasing and differentiable, $\xi^{(1)}(\cdot)$ must be strictly positive and bounded on $[\eta_T, s^*]$. Hence we can write $\xi^{(1)}(\eta^*) \in [\bar{\alpha}_1, \alpha_1]$ where $\bar{\alpha}_1 > \alpha_1 > 0$.

Since $\xi(\cdot)$ is either strictly concave or strictly convex on $[\eta_T, s^*]$, we have $\xi^{(1)}(\cdot)$ is either strictly decreasing or strictly increasing. Since it is also differentiable, it follows that $\xi^{(2)}(\cdot)$ must be either strictly negative or strictly positive on $[\eta_T, s^*]$, and that it is bounded. Hence we can write $\xi^{(2)}(\eta^*) \in [\bar{\alpha}_2, \alpha_2]$ where $\bar{\alpha}_2 > \alpha_2$. And $\alpha_2$ and $\bar{\alpha}_2$ are both negative (if $\xi(\cdot)$ is strictly concave) or both negative (if $\xi(\cdot)$ is strictly convex). \qed

Lemma 4. Let $s^* > \eta_T$. Define $M_k(\eta^*) = \frac{\xi^{(k)}(\eta^*)}{(\rho_T + \rho_i)^k}$ for non-negative integers $k \leq 3$.

- When $k \in \{0, 1\}$, $M_k(\eta^*)$ is strictly positive for any $\rho_T > 0$ and $\rho_i > 0$
- $M_2(\eta^*)$ is either strictly positive or strictly negative
- There exists $r_0$ such that $\rho_T + \rho_i > r_0$ implies $|M_1(\eta^*)| > \rho_i(s^* - \eta_T)|M_2(\eta^*)|$
- When $k \in \{0, 1, 2\}$, for any small $\epsilon > 0$, there exists $R_k(\epsilon)$ such that $\rho_T + \rho_i > R_k(\epsilon)$ implies $(1 - \epsilon)|M_k(\eta^*)| > \frac{1}{2} |M_{k+2}(\eta^*)|

Proof. When $\rho_T > 0$ and $\rho_i > 0$, $M_k(\eta^*)$ is strictly positive for any $k \in \{0, 1\}$ as a direct result of Lemma 3; $M_2(\eta^*)$ is either strictly positive or strictly negative as a direct result of Lemma 3.

For $k \in \{0, 1\}$. Let

$$R_k(\epsilon) = \sqrt{\frac{\max_{\eta \in [\eta_T, s^*]} |\xi^{(k+2)}(\eta)|}{2(1 - \epsilon)\alpha_k}}$$
Then whenever \( \rho_T + \rho_i > R_k(\epsilon) \), we have

\[
(\rho_T + \rho_i)^2 > R_k(\epsilon)^2 \quad (12)
\]

\[
= \frac{\max_{\eta \in \tilde{\eta}_T, s^*} |\xi^{(k+2)}(\eta)|}{2(1-\epsilon)\alpha_k} \quad (13)
\]

\[
\geq \frac{|\xi^{(k+2)}(\tilde{\eta}^*)|}{2(1-\epsilon)|\xi^{(k)}(\tilde{\eta}^*)|} \quad (14)
\]

Rearrange the above and it is exactly

\[
(1 - \epsilon) |M_k(\tilde{\eta}^*)| > \frac{1}{2} |M_{k+2}(\tilde{\eta}^*)|
\]

Similarly, we can show that by letting

\[
R_2(\epsilon) = \sqrt{\frac{\min_{\eta \in \tilde{\eta}_T, s^*} |\xi^{(4)}(\eta)|}{2(1-\epsilon)\max \{|a_2|, |\tilde{a}_2|\}}}
\]

Whenever \( \rho_T + \rho_i > R_2(\epsilon) \), it follows that

\[
(1 - \epsilon) |M_2(\tilde{\eta}^*)| > \frac{1}{2} |M_4(\tilde{\eta}^*)|
\]

Similarly, we can show that by letting

\[
r_0 = \frac{\rho_i(s^* - \tilde{\eta}_T) \max_{\eta \in \tilde{\eta}_T, s^*} |\xi^{(2)}(\eta)|}{\alpha_1}
\]

Whenever \( \rho_T + \rho_i > r_0 \), it follows that

\[
|M_1(\tilde{\eta}^*)| > \rho_i(s^* - \tilde{\eta}_T) |M_2(\tilde{\eta}^*)|
\]

\[\square\]

**Lemma 5.** Let \( s^* > \tilde{\eta}_T \). When \( M_k(\tilde{\eta}^*) = \frac{\xi^{(k)}(\tilde{\eta}^*)}{(\rho_T + \rho_i)^k} \) and \( R_k(\cdot) \) and \( r_0 \) are as defined in Lemma 4. Then

- \( \frac{\partial M_k(\tilde{\eta}^*)}{\partial \rho_T} \) is strictly negative.

- \( \frac{\partial M_1(\tilde{\eta}^*)}{\partial \rho_T} \) is strictly negative when \( \rho_T + \rho_i > r_0 \) where \( r_0 \) is as defined in Lemma 4.
\begin{itemize}
    
    \item For \( k \in \{0, 1\} \), any small \( \epsilon > 0, \delta > 0 \). Define \( \delta_0 = \frac{(\rho_T + \rho_t)\delta}{\rho_t(s^* - \eta_T)} \). \( M = \min \{M_{k+2}(\eta^*), M_{k+3}(\eta^*)\} \) and \( \epsilon_0 = \frac{\epsilon M + 20\delta_0(1-\epsilon)}{M + \delta_0(1-\epsilon)} \). Then whenever \( \rho_T + \rho_t > R_k(\epsilon_0) \), we have

\[
    \left| \frac{\partial M_k(\eta^*)}{\partial \rho_T} \right| > \frac{1}{2(1-\epsilon)} \left| \frac{\partial M_{k+2}(\eta^*)}{\partial \rho_T} \right| + \delta
\]

\end{itemize}

**Proof.** Write \( M_k(\eta^*) = \frac{\xi^{(k)}(\eta^*)}{(\rho_T + \rho_t)^*} \) and \( \frac{\partial \eta^*}{\partial \rho_T} = \frac{\rho_t(\eta_T - s^*)}{(\rho_T + \rho_t)^*} \). Hence for \( k \in \{0, 1\} \), we can derive

\[
    \frac{\partial M_k(\eta^*)}{\partial \rho_T} = - \frac{1}{\rho_T + \rho_t} \left( \rho_t(s^* - \eta_T)M_{k+1}(\eta^*) + kM_k(\eta^*) \right)
\]

By Lemma 4, \( M_1(\eta^*) \) is strictly positive. Since \( s^* - \eta_T > 0, \rho_T > 0 \) and \( \rho_t > 0 \), it follows that \( \frac{\partial M_0(\eta^*)}{\partial \rho_T} \) is strictly negative. When \( \rho_T + \rho_t > \rho_0 \), we have that \( M_1(\eta^*) + \rho_t(s^* - \eta_T)M_2(\eta^*) > \rho_t(s^* - \eta_T)[|M_2(\eta^*)| - M_2(\eta^*)] \geq 0 \). Hence \( \frac{\partial M_0(\eta^*)}{\partial \rho_T} \) is strictly negative.

Also by Lemma 4, when \( k \in \{0, 1\} \) and \( \rho_T + \rho_t > \max \{R_k(\epsilon_0), R_{k+1}(\epsilon_0)\} \),

\[
    M_k(\eta^*) > \frac{1}{2(1-\epsilon_0)} |M_{k+2}(\eta^*)| \geq \frac{1}{2(1-\epsilon)} |M_{k+2}(\eta^*)| + \delta_0
\]

\[
    M_{k+1}(\eta^*) > \frac{1}{2(1-\epsilon_0)} |M_{k+3}(\eta^*)| \geq \frac{1}{2(1-\epsilon)} |M_{k+3}(\eta^*)| + \delta_0
\]

Hence

\[
    \frac{\partial M_k(\eta^*)}{\partial \rho_T} < - \frac{\rho_t(s^* - \eta_T)|M_{k+3}(\eta^*)| + k|M_{k+2}(\eta^*)|}{2(1-\epsilon)(\rho_T + \rho_t)} - \frac{\delta_0(\rho_t(s^* - \eta_T) + k)}{\rho_T + \rho_t}
\]

\[
    = - \frac{\rho_t(s^* - \eta_T)|M_{k+3}(\eta^*)| + k|M_{k+2}(\eta^*)|}{2(1-\epsilon)(\rho_T + \rho_t)} - \delta
\]

\[
    \leq - \frac{|\rho_t(s^* - \eta_T)M_{k+3}(\eta^*) + kM_{k+2}(\eta^*)|}{2(1-\epsilon)(\rho_T + \rho_t)} - \delta
\]

\[
    = - \frac{1}{2(1-\epsilon)} \left| \frac{\partial M_{k+2}(\eta^*)}{\partial \rho_T} \right| - \delta
\]

Therefore,

\[
    \left| \frac{\partial M_k(\eta^*)}{\partial \rho_T} \right| > \frac{1}{2(1-\epsilon)} \left| \frac{\partial M_{k+2}(\eta^*)}{\partial \rho_T} \right| + \delta
\]

\[\square\]

**Theorem 2.** Assume \( \theta + \Delta > \bar{\eta}_T \). When \( \rho_T \) is sufficiently large, \( \text{EffectSize}(\bar{\eta}_T, \sigma_T^2) \) decreases in \( \rho_T \). When \( \xi(\cdot) \) is the identity function, this holds for all positive values of \( \rho_T \).

**Proof.** \( \text{EffectSize}(\bar{\eta}_T, \sigma_T^2) \) can be written as
EffectSize(\(\bar{\eta}_T, \sigma_T^2\)) = \(\frac{\rho_c}{\sigma_c} \left[ \frac{\xi(1)(\bar{\eta}^*)}{\rho_T + \rho_c} + \frac{\xi(3)(\bar{\eta}^*)}{2(\rho_T + \rho_c)^2} \right] \phi \left( \frac{1}{\sigma_c} \left[ \frac{\xi(1)(\bar{\eta}^*)}{\rho_T + \rho_c} + \frac{\xi(2)(\bar{\eta}^*)}{2(\rho_T + \rho_c)^2} - c \right] \right) \) (23)

Where \(\phi(\cdot)\) is the probability density function of a standard normal variable \(z \sim N(0,1)\). Write \(\bar{\eta}^* = \frac{\rho_T \bar{\eta} + \rho_c(\theta_0 + \Delta)}{\rho_T + \rho_c}\) and \(M_k(\bar{\eta}^*) = \xi(\bar{\eta}^*)^{(k)}(\bar{\eta}^*)\). Also define \(\epsilon(\rho_T) = 1 - \left( \frac{\rho_c}{\rho_T + \rho_c} \right)^2 \in (0,1)\). Note that \(\epsilon'(\rho_T) < 0\) and \(\frac{\epsilon'(\rho_T)}{2(1 - \epsilon(\rho_T))^2} = -\frac{\rho_c^2 \Delta^2}{(\rho_T + \rho_c)^2}\) which decreases in \(\rho_T\) and shrinks to 0 when \(\rho_T \to \infty\). Hence \(\forall \delta > 0\), there exists \(Q(\delta) = \max \left\{ 0, \frac{(1 + \sqrt{1 + 4\delta}) \rho_c^2 \Delta^2 - \rho_c}{2} \right\}\) such that whenever \(\rho_T > Q(\delta)\), we have \(\left| \frac{\epsilon'(\rho_T)}{2(1 - \epsilon(\rho_T))^2} \right| < \delta\). Then

\[\text{EffectSize}(\bar{\eta}_T, \sigma_T^2) = \frac{\rho_c}{\sigma_c} \left[ M_1(\bar{\eta}^*) + \frac{M_3(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))} \right] \phi \left( \frac{1}{\sigma_c} \left[ M_0(\bar{\eta}^*) + \frac{M_2(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))} - c \right] \right)\] (24)

Consider the comparative static

\[\frac{\partial \text{EffectSize}(\bar{\eta}_T, \rho_T)}{\partial \rho_T} = \frac{\rho_c}{\sigma_c} \phi \left( \frac{1}{\sigma_c} \left[ M_0(\bar{\eta}^*) + \frac{M_2(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))} - c \right] \right) \left( M_0(\bar{\eta}^*) + \frac{M_2(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))} \right) \left( c - M_0(\bar{\eta}^*) - \frac{M_2(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))} \right) \right) \left( \frac{\partial M_1(\bar{\eta}^*)}{\partial \rho_T} + \frac{\partial M_3(\bar{\eta}^*)}{\partial \rho_T} - \frac{M_3(\bar{\eta}^*) \epsilon'(\rho_T)}{2(1 - \epsilon(\rho_T))^2} \right) \left( M_0(\bar{\eta}^*) + \frac{M_2(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))} \right) \left( c - M_0(\bar{\eta}^*) - \frac{M_2(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))} \right) \right) \left( \frac{\partial M_0(\bar{\eta}^*)}{\partial \rho_T} + \frac{\partial M_2(\bar{\eta}^*)}{\partial \rho_T} - \frac{M_2(\bar{\eta}^*) \epsilon'(\rho_T)}{2(1 - \epsilon(\rho_T))^2} \right) \left( \frac{\partial M_0(\bar{\eta}^*)}{\partial \rho_T} + \frac{\partial M_3(\bar{\eta}^*)}{\partial \rho_T} - \frac{M_3(\bar{\eta}^*) \epsilon'(\rho_T)}{2(1 - \epsilon(\rho_T))^2} \right) \right) \left( \frac{\partial M_0(\bar{\eta}^*)}{\partial \rho_T} + \frac{\partial M_3(\bar{\eta}^*)}{\partial \rho_T} - \frac{M_3(\bar{\eta}^*) \epsilon'(\rho_T)}{2(1 - \epsilon(\rho_T))^2} \right) \] (27)

Let \(M = \min \{M_2(\bar{\eta}^*), M_3(\bar{\eta}^*)\}\). \(\forall \delta > 0\), when \(\rho_T > Q\left(\frac{\delta}{M}\right)\), it follows that for \(k \in \{0, 1\}\),

\[\left| \frac{\epsilon'(\rho_T)}{2(1 - \epsilon(\rho_T))^2} \right| < \frac{\delta}{M_{k+2}(\bar{\eta}^*)} \] (28)

Choose \(\delta_0 = \frac{(\rho_T + \rho_c) \epsilon_0}{\rho_c (s^* - \eta_T)} + 1\) and \(\epsilon_0 = \frac{\epsilon(\rho_T) M + 2 \delta_0 (1 - \epsilon(\rho_T))}{M + 2 \delta_0 (1 - \epsilon(\rho_T))}\). Then when \(\rho_T > R_k(\epsilon_0) - \rho_c\), we have that for \(k \in \{0, 1\}\),

\[\frac{\partial M_k(\bar{\eta}^*)}{\partial \rho_T} + \frac{\partial M_{k+2}(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))^2} - \frac{M_{k+2}(\bar{\eta}^*) \epsilon'(\rho_T)}{2(1 - \epsilon(\rho_T))^2} < -\delta + \delta = 0 \] (29)

Additionally, \(\left( M_1(\bar{\eta}^*) + \frac{M_3(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))} \right) \left( c - M_0(\bar{\eta}^*) - \frac{M_2(\bar{\eta}^*)}{2(1 - \epsilon(\rho_T))} \right) > 0\). Combining all these inequalities gives

\[\frac{\partial \text{EffectSize}(\bar{\eta}_T, \rho_T)}{\partial \rho_T} < 0 \] (30)

69
The remainder of the problem boils down to choosing an appropriately balanced $\delta > 0$ such that the threshold for $\rho_T$ is minimized. More precisely, this is when

$$Q \left( \frac{\delta}{M} \right) = \max_{k \in \{0,1,2\}} R_k(\epsilon_0) - \rho_t$$

When $\xi(\cdot)$ is the identity, derivatives of order higher than 1 are all zero. In this case $\epsilon_0$ can be arbitrarily close to 1 since $R_k(\epsilon) = 0$ for $k = 0,1,2$. This means that $\delta_0$ can be arbitrarily large and hence $\delta$ can be arbitrarily large. Then the desired inequality holds for all values of $\rho_T > 0$.

A1 Appendix Tables

Table A1: Selected Parameter Estimates of Poisson Model for End of Launch Day Upvotes

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year of Training Data</td>
<td>2013 - 2014</td>
<td>2015</td>
<td>2016</td>
<td>2017</td>
</tr>
<tr>
<td>Featured</td>
<td>0.661</td>
<td>2.213</td>
<td>2.647</td>
<td>2.857</td>
</tr>
<tr>
<td>Makers Count</td>
<td>0.008</td>
<td>0.072</td>
<td>0.086</td>
<td>0.062</td>
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<tr>
<td>Has Maker</td>
<td>0.907</td>
<td>0.441</td>
<td>0.311</td>
<td>0.278</td>
</tr>
<tr>
<td>Has iPhone App</td>
<td>-0.058</td>
<td>-0.006</td>
<td>-0.001</td>
<td>-0.006</td>
</tr>
<tr>
<td>Has Android App</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.011</td>
<td>-0.048</td>
</tr>
<tr>
<td>Images Count</td>
<td>0.017</td>
<td>0.009</td>
<td>0.023</td>
<td>0.026</td>
</tr>
<tr>
<td>Videos Count</td>
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<td>0.012</td>
<td>0.021</td>
<td>0.023</td>
</tr>
<tr>
<td>Audios Count</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.040</td>
<td>-0.607</td>
</tr>
<tr>
<td>External Articles Count</td>
<td>-0.004</td>
<td>0.032</td>
<td>0.134</td>
<td>0.102</td>
</tr>
<tr>
<td>Description Length (Hundred Words)</td>
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<td>0.421</td>
<td>0.211</td>
<td>0.074</td>
</tr>
<tr>
<td>Tagline Length (Words)</td>
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<td>0.002</td>
<td>0.000</td>
<td>0.005</td>
</tr>
<tr>
<td>Hunters' Followers (Thous.)</td>
<td>0.043</td>
<td>0.013</td>
<td>0.021</td>
<td>0.012</td>
</tr>
<tr>
<td>Hunets' Featured Hunts (Thous.)</td>
<td>1.666</td>
<td>0.067</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Hunters' Upvotes on Featured Products (Thous.)</td>
<td>0.000</td>
<td>0.000</td>
<td>0.008</td>
<td>0.027</td>
</tr>
<tr>
<td>Hunter is Special Contributor</td>
<td>0.121</td>
<td>0.082</td>
<td>0.263</td>
<td>0.081</td>
</tr>
<tr>
<td>Optimal Regularization Strength (1se)</td>
<td>0.626</td>
<td>1.008</td>
<td>0.719</td>
<td>0.842</td>
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<td>Number of Observations</td>
<td>12235</td>
<td>31576</td>
<td>39531</td>
<td>28882</td>
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<tr>
<td>Outcome Average</td>
<td>30.519</td>
<td>34.180</td>
<td>33.603</td>
<td>50.494</td>
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<tr>
<td>Outcome Standard Deviation</td>
<td>52.584</td>
<td>78.861</td>
<td>89.478</td>
<td>120.569</td>
</tr>
</tbody>
</table>

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 – 2014, 2015, 2016, and 2017 respectively). Optimal regularization parameter $\lambda$ is also presented in each column. Training data sizes, and the mean and standard deviation of the outcome variable in the training data are also shown at the bottom of the table.
Table A2: Effect of Product Rank on Early Stage VC Funding Within 6 Months

<table>
<thead>
<tr>
<th></th>
<th>OLS (1)</th>
<th>OLS (2)</th>
<th>OLS (3)</th>
<th>OLS (4)</th>
<th>OLS (5)</th>
<th>IV/2SLS (3)</th>
<th>IV/2SLS (4)</th>
<th>IV/2SLS (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Product Daily Rank</strong></td>
<td><strong>0.0018</strong>*</td>
<td><strong>0.0111</strong>*</td>
<td><strong>0.0109</strong>*</td>
<td><strong>0.0113</strong>*</td>
<td><strong>0.0118</strong>*</td>
<td><strong>0.0118</strong>*</td>
<td><strong>0.0118</strong>*</td>
<td><strong>0.0118</strong>*</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0055)</td>
<td>(0.0058)</td>
<td>(0.0062)</td>
<td>(0.0062)</td>
<td>(0.0062)</td>
<td>(0.0062)</td>
<td>(0.0062)</td>
</tr>
<tr>
<td><strong>First Stage Dependent Variable: Product Daily Rank</strong></td>
<td><strong>-0.7912</strong>*</td>
<td><strong>-0.7367</strong>*</td>
<td><strong>-0.7001</strong>*</td>
<td><strong>-0.7045</strong>*</td>
<td><strong>-0.7045</strong>*</td>
<td><strong>-0.7045</strong>*</td>
<td><strong>-0.7045</strong>*</td>
<td><strong>-0.7045</strong>*</td>
</tr>
<tr>
<td></td>
<td>(0.1705)</td>
<td>(0.1518)</td>
<td>(0.1498)</td>
<td>(0.1494)</td>
<td>(0.1494)</td>
<td>(0.1494)</td>
<td>(0.1494)</td>
<td>(0.1494)</td>
</tr>
</tbody>
</table>

**Notes:** Result table shows the effects of Product Hunt daily ranking on early-stage funding in 6 months after product launch. All specifications control for weekly cyclicality and year-quarter fixed effects. Column 2 additionally controls for firm characteristics, including CrunchBase classified categories, firm age quarter fixed effects, headquarter location, and previous funding (seed, convertible note and venture) rounds and amount as well as weeks elapsed since last funded. Column 2 also controls for characteristics of founding and executive teams, including size, female share, share that had founded companies before, and share that had employed at “big five” software companies, i.e. Apple, Amazon, Google, Microsoft and Facebook. Column 3 additionally controls for Product Hunt launch characteristics, including the hunter’s influence – number of followers at launch, gender, whether hunter is an entrepreneur, investor, or senior management at startups, whether hunter links Twitter account, and whether hunter has a headline, launch time of day fixed effects in 10 minute buckets, number of external articles linked to the launch, whether product post has a thumbnail picture, and number of image, video and audio content pieces. Column 4 adds a more stringent time fixed effects control at the year-month level. Column 5 focuses on products that are launched yesterday before the daily feed upvote competition begins, and moved to be featured today. Column 6 focuses on product posts submitted by an external “hunter”, who is not a member of the product maker team. All specifications report robust standard errors. OLS estimates and first stage results and F-statistics are reported alongside the IV estimates in each column.
<table>
<thead>
<tr>
<th></th>
<th>OLS (1)</th>
<th>OLS (2)</th>
<th>OLS (3)</th>
<th>OLS (4)</th>
<th>OLS (5)</th>
<th>OLS (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Daily Rank</td>
<td>-0.0001</td>
<td>0.0004</td>
<td>0.0006</td>
<td>0.0000</td>
<td>-0.0002</td>
<td>0.0067</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0021)</td>
<td>(0.0019)</td>
<td>(0.0018)</td>
<td>(0.0019)</td>
<td>(0.0029)</td>
</tr>
</tbody>
</table>

**Table A3: No Effect of Product Rank on Venture Rounds Within 6 Months**

<table>
<thead>
<tr>
<th></th>
<th>IV/2SLS (4)</th>
<th>IV/2SLS (5)</th>
<th>IV/2SLS (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.0002</td>
<td>-0.0067</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0019)</td>
<td>(0.0029)</td>
<td></td>
</tr>
</tbody>
</table>

**First Stage Dependent Variable: Product Daily Rank**

<table>
<thead>
<tr>
<th>Traction Weighted Moved Posts</th>
<th>-1.7877***</th>
<th>-1.9809***</th>
<th>-2.0107***</th>
<th>-1.9952***</th>
<th>-3.8471***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.2784)</td>
<td>(0.2553)</td>
<td>(0.2543)</td>
<td>(0.2566)</td>
<td>(0.6660)</td>
</tr>
</tbody>
</table>

**Controls: Weekly Cyclicality**
- Y

**Controls: Post Characteristics**
- N

**Controls: Firm Characteristics**
- N

**Controls: Founder Characteristics**
- N

**Fixed Effects**
- Year-Month
- Year-Month
- Year-Month
- Year-Month
- Year-Month
- Year-Month

**Sample**
- All

**Number of Observations**
- 7664

**Mean Outcome**
- 0.037

**Median Rank**
- 13

**R^2**
- 0.026

**First Stage F-Statistic**
- 94.252

**Notes:** Result table shows the effects of Product Hunt daily ranking on venture rounds in 6 months after product launch. All specifications control for weekly cyclicality and year-quarter fixed effects. Column 2 additionally controls for firm characteristics, including CrunchBase classified categories, firm age quarter fixed effects, headquarter location, and previous funding (seed, convertible note and venture) rounds and amount as well as weeks elapsed since last funded. Column 2 also controls for characteristics of founding and executive teams, including size, female share, share that had founded companies before, and share that had been employed at “big five” software companies, i.e. Apple, Amazon, Google, Microsoft and Facebook. Column 3 additionally controls for Product Hunt launch characteristics, including the hunter’s influence – number of followers at launch, gender, whether hunter is an entrepreneur, investor, or senior management at startups, whether hunter links Twitter account, and whether hunter has a headline, launch time of day fixed effects in 10 minute buckets, number of external articles linked to the launch, whether product post has a thumbnail picture, and number of image, video and audio content pieces. Column 4 adds a more stringent time fixed effects control at the year-month level. Column 5 focuses on products that are launched yesterday before the daily feed upvote competition begins, and moved to be featured today. Column 6 focuses on product posts submitted by an external “hunter”, who is not a member of the product maker team. All specifications report robust standard errors. OLS estimates and first stage results and F-statistics are reported alongside the IV estimates in each column.