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

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Abstract

A recent explosion in startup activity, often linked to reduced experimentation costs, has made it challenging for venture capital (VC) firms to efficiently obtain information and perform due diligence. This paper explores frictions in the process of venture capital information acquisition using micro data from Product Hunt, an online platform covering a large number of technology startups’ product launches. On a daily basis, launched products compete for ranking based on user upvotes – a crowdsourced measure of expected consumer demand. I document that exogenously raising a product by 1 rank improves the underlying firm’s funding probability within the next 6 months by 9.2% relative to a base rate of 6.8%. Launching a highly ranked product is correlated with subsequent faster deal closing, more experienced lead investor, and larger funding amount. The effect of product rank is twice as large for first-time entrepreneurs, and mainly driven by firms located away from venture capital hubs. I develop a theoretical model of venture capital decision making to explain these differential effects. The model predicts that crowd-sourced signals carry a larger decision weight when VCs evaluate more risky startups with less ex-ante available information.

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1 Introduction

Venture capital facilitates cutting-edge innovations through funding startup companies with the potential to generate lasting impact on consumer welfare. Today’s most influential public companies were initially backed by venture capital, such as Apple and Amazon, whose products and services have revolutionized industry landscape and reshaped consumer habits. Venture capital investors help bring path-breaking technologies to the market, and contribute to decisions of entrepreneurial firms through guidance and monitoring. A large literature studying innovation and entrepreneurship has 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).

Information asymmetry is a central challenge faced by venture capital investors, since entrepreneurial firm insiders know more about their own quality and effort than the venture capitalist. Frictions in the process of acquiring information can lead VCs to make inefficient funding decisions. These frictions may cause factors unrelated to firm fundamentals to weigh in, and generate persistent differences in outcomes of innovative firms and ultimately affect their chances of a successful exit through IPOs and mergers. When potentially impactful ideas face difficulty in securing early-stage funding, the startup may not be able to realize its full value in the long run.

In the context of rising startup activity seeking initial funding, does the way in which information about these startups is presented, independent of firm fundamentals, affect venture capitalists’ funding decisions? And is the effect of limited investor attention especially pronounced when investors face a rising number of potential deals to screen? I explore these issue using micro data from Product Hunt – a large online platform widely used by tech workers, entrepreneurs and investors, which crowdsources signals of product traction from potential consumers on a daily basis. As a crowdsourced and centralized information exchange on startups’ latest products, Product Hunt allows quick daily comparisons among launched products by ranking them according to user upvotes. It provides readily available and easily digestible information to VCs faced with an increasing number of potential investments.

I first document correlational evidence that being prominently featured on Product Hunt is associated with strong improvement in startups’ subsequent funding outcomes. I focus on the startups’ chance of obtaining early-stage VC funding, i.e. seed, convertible note, and series A. Being top ranked predicts a much higher funding probability within the first 6 months of launching a product on Product Hunt. Conditional on being funded in the next year, firms with more highly ranked products close deals at a faster pace, and obtain a larger amount of investment led by
more experienced VC firms. These findings are consistent with anecdotal evidence arising from conversation with practitioners as well as online blog posts and news articles, which suggest that VC investors source deals through Product Hunt. Despite these signals being potentially noisy, investors still incorporate them in evaluating potential deals.

In addition to documenting a clear strong correlation between product rank and venture capitalists’ funding decisions in the aftermath, I estimate the causal effect of product ranking by exploiting exogenous shifts to daily product rank through two separate sources of variation. First, startup firms launching products on Product Hunt cannot anticipate that a major technology company such as Apple or Facebook will release new products around the same time. These new products are often shared to Product Hunt feed concurrently with an official announcement or major media coverage (e.g. a CNBC news article). These unexpected high-impact product posts absorb upvoter attention and push down the rankings of other products launched by startup firms, since major tech firms’ products are almost always highly upvoted and top ranked. These top firms also have no incentive to release products at a strategic time to cater specifically to the Product Hunt community.

The same intuition guides another identification approach, which relies on the fact that Product Hunt staff move a non-trivial number of products from previous days into today’s feed in an exogenous manner. 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 calculate an instrument as the sum of “predicted traction” of products moved into to today’s feed. “Predicted traction” measures the impact of moved products more accurately than raw counts, since higher-impact products will end up with a higher rank and affect a larger number of other products launched on the same day.

Using these instrumental variable strategies, I estimate that when the average product’s rank moves up by 1 place, the funding probability increases by 9.2% relatively to a base rate of 6.8% in the next 6 months. For example, if a median ranked (13th) product 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 11.6%. Improving product rank particularly affects startup firms that may face larger barriers to accessing venture capital. The effect of product rank is twice as large for startups founded by first-time entrepreneurs compared to experienced founders, and the effects are mainly driven by firms located away from venture capital hotspots – San Francisco Bay Area, New York City and London. Product Hunt facilitates access to venture capital among startups that may otherwise
go unnoticed, and gives them a chance to showcase product traction by gaining a large number of community upvotes and becoming top ranked.

Given that venture capitalists specialize in overcoming information asymmetries, it may be surprising that crowd signals should have a significant effect on funding decisions. I develop a theoretical model of early-stage VC decision making that grounds this effect in a signal acquisition and learning framework, in which VCs collect information about startup profitability over time, and update beliefs about the distribution of returns from the investment. The model mirrors frequently used early-stage venture valuation methods in practice, such as step-up and risk mitigation. These methods involve making a checklist of milestones, and adding up dollar amounts at the completion of each milestone to reach a valuation.

The model predicts that crowd-sourced signals carry heterogeneous decision weights when VCs make funding decisions for different kinds of start-ups. When VCs are ex-ante less certain about an early-stage business, e.g. when evaluating firms founded by first-time entrepreneurs, or when the venture capital firm is located away from the startup headquarter, the added signal from Product Hunt crowd is taken into consideration with a larger weight. The Product Hunt signal becomes more relevant than usual 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 paper contributes to a few strands of literatures. First, it sheds light on the information acquisition process of early-stage venture capital investors, and adds to the understanding of the determinants of their investment decisions (Shepherd, 1999; Kaplan and Strömberg, 2003; Kaplan et al., 2009; Gompers et al., 2016a; Bernstein et al., 2017). An experimental or quasi-experimental setting is rare to come by in past research on this topic, since it is hard to investigate the causal role of information which may correlate with other factors that are hard to separate without running an experiment. Hence the canonical literature on this topic takes a descriptive approach (Gompers, 1995). The paper estimates the causal effect of information frictions by leveraging features of a widely used online platform among VC investors, which generates sources of exogenous variation in products’ visibility and status, and enables sharp identification of the causal effect of information presentation about startup products. It provides concrete empirical evidence that frictions in the process of venture capital information acquisition have real effects on the VC investors’ decision to finance early-stage technology startups.

Second, 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, works that document similar designs of online markets that shape financial investments have been dearth. This paper describes how information aggregation on Product Hunt influences investor behavior, and provides empirical evidence for the causal effect of information on this online platform on early-stage venture investments. This is particularly relevant given the recent trend among early-stage VCs to experiment with making small investments in the face of a large surge in early-stage startups seeking money (Kerr et al., 2014; Kerr and Nanda, 2015; Ewens et al., 2018).

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

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

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 traditional databases that collect information at a time lag (Baron and Hannan, 2002; Reuters, 2011), Product Hunt aggregates contemporaneous product offerings which allow researchers to study up-to-date patterns of innovative activities among technology startups. As venture capitalists and other investors observe most up-to-date information about these firms and make investment decisions based on such information, measuring products contemporaneously captures the role of the “jockey” more accurately in measuring determinants to venture capitalists’ decisions.

The remainder of the paper is structured as follows. Section 2 describes data collection, and provides descriptive statistics on the regression sample. Section 3 illustrates the correlation between Product Hunt rankings and venture capital funding, and discusses anecdotal evidence that VCs use Product Hunt to source deals. Section 4 provides two identification strategies to measure exogenous shifts to product ranks, and the resulting information frictions. Section 5 presents empirical estimates of the causal effect of exogenous shifts to product rank on firms’ subsequent funding probability, and shows 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. Section 7 concludes with a discussion of potential future research directions.

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 from when Product Hunt was founded to March 2018, by crawling its 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 describe the product launch process. I 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 the same 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. Product and feature releases of major software companies including FAGMA (Facebook, Amazon, Google, Microsoft and Apple) are often announced to Product Hunt as soon as they become official. Contributed by thousands of users, Product Hunt provides the most up-to-date product information in the tech industry. Figure 1 shows an example of a recent product launch – Amazon Scout, launched on Product Hunt immediately after a CNBC story initially covered the new release by Amazon.

Being a startup company itself, Product Hunt gained prominence shortly after it was founded and had sustained success. TechCrunch awarded Product Hunt the “Best New Startup” of 2014. In the same year, Product Hunt closed a series A funding deal of $6.1 million led by prestigious venture capital firm Andreessen Horowitz. More recently 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.

Currently, Product Hunt has over a million users and more than 80 daily product submissions on average. Figure 2 shows the growth of Product Hunt user base from founding to 2018Q1. Panel A shows the growth in the total number of users, and Panel B focuses on users who have been active in the past 90 days\(^1\). Both the total number of users and the number of users have increased steadily since Product Hunt was founded, and past 90-day active users account for about 10% of the overall user base.

User activities on Product Hunt are powered entirely by community members, who submit the products, upvote them and comment on these products. All users can participate in upvoting products, while submitting and commenting requires becoming a contributor, which involves a straightforward process that any user can easily complete within a few days. Being 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 the page. This is especially compelling for busy entrepreneurs and investors, who may prefer consuming quick run-down of top products in a condensed list or daily digest. The platform gives particular visibility to the most frequently upvoted popular products, by ranking products according to total user upvotes on a daily basis.

\(^1\)Active users have submitted, upvoted or commented on at least one product.
The Product Hunt community consists of entrepreneurs, innovators and investors, and predominantly individuals who work in the tech industry. I use self-identifying information from users’ names and headlines to get a sense of whom the active contributors to Product Hunt are. A majority of active users (71%) registered their Product Hunt profiles using real names, which allows for determining demographic variables such as gender. I parse the username and classify parts appropriately as “given name”, “surname”, or “corporate name”, and then use an online tool to determine the gender of each given name\(^2\). After conducting these classification procedures, only about 25% of active Product Hunt users are female.

Over 40% of the users have non-empty headlines describing organizational roles and/or affiliations, which allow me to infer the occupations of these users. Figure 3 lists the most common phrases (1- and 2-grams) in these headlines, ranked according to relative frequency.\(^3\) The most common headline key phrases are “developer”, “designer”, “founder”, “product” and “ceo”, which account for close to 40% of users with non-empty headlines. Common headlines suggest affiliation with the tech sector and startup companies, (indicated by the prevalence of phrases such as “developer”, “software engineer”, “ux”, “web”, etc), and a non-trivial population are entrepreneurs and senior managers of startup firms (indicated by phrases such as “founder”, “ceo”, “manager”, “director”, etc).

I label Product Hunt users as entrepreneurs, senior managers or investors, using self-identifying information contained in their headlines. Entrepreneurs are defined as users whose headlines contain phrases such as “founder”, “co-founder”, and “entrepreneur”. Senior managers are defined as users whose headlines contain phrases such as “ceo”, “director”, “president”, “vice president”, “owner”, “vp”, “coo”, “cfo”, “cmo”, and “cto”. Investors are defined as users whose headlines contain phrases such as “investor”, “investment”, “venture”, “capital”, and “fund”. Some users serve multiple roles, for example, startup founders are sometimes also CEOs of the company that they founded, and hence they are labeled as both entrepreneurs and senior managers. By these definitions, at least 14% of self-identifying users are entrepreneurs, 14% are in senior managers, and 1.5% are investors or work at an investment organization.

\(^2\)Python package “probablepeople” is used to parse and classify parts of the names appropriately, and the “genderize.io” API is called to detect genders of parsed given names.

\(^3\)I perform the standard text processing procedure on user headlines. This involves turning the text to lower case, removing special characters and stopwords (e.g. “the”) in standard NLP package dictionary.
2.2 Product Launch Process

Launching a product on Product Hunt entails a straight-forward process. The “hunter”, usually an influencer or one of the product makers\(^4\), submits the product by collecting a list of items including product name and details as well as a link to the product’s website, among other things. Product details include a descriptive text, as well as media information such as images, videos, audios if posted product is a podcast episode and book reviews if posted product is a book. Sometimes, there can be multiple web links to a product post, e.g. links to different app platforms such as iPhone and Android, or links to Kickstarter campaign for companies that also host their own separate websites. Sometimes, the web links are news articles and blog posts describing the product. The “hunter” can tag a product by appropriate topics (such as “Tech”, “Productivity”, “Health and Fitness”, etc) which identify the product’s sector or category. If members of the product team are registered Product Hunt users, they can be identified as “makers” of the product.

After launching a product, the “hunter” and “makers” usually kick off a discussion about the product by posting comments to the launched post. These comments usually contain further description of the product and a welcome message to the Product Hunt community to encourage feedback and discussion. Users can upvote the product at most once, and interact with other users also interested in the product by posting comments. Although product posts remain open to upvotes and comments after the launch day, it typically has the most user views and hence the largest probability to attract upvotes on the launch day. In fact, most products attain over 50% of lifetime upvotes within 24 hours of launching. Upvotes become much more sporadic once the launch day ends, and when the product is no longer on the daily feed of “popular” or “newest” products.

Almost all launched products start on the daily “newest” feed, and the Product Hunt community team will select about a third of the products to put on the “popular” feed (i.e. the front page), where the products will compete for ranking by gathering authentic community upvotes. Being selected to post on the front page is called being “featured” on Product Hunt, and this decision mainly depends on the speed at which the product gains upvotes from users after being launched. However, the decision takes many factors into consideration, and is not completely automatic or based on fixed criteria. Product Hunt typically features a product within a few hours after the product has been launched, and aims to identify the highest traction products with the

\(^4\)All users can participate in upvoting products, but only verified “contributors” can submit products and post comments. The “contributor” status is accessible to any online user and can be obtained within a few days. Specifically, it involves upvoting 11 products, upvoting products for three days in a row, and writing a profile headline. Once the user is verified as a “contributor”, no further activity is required to maintain this status.
most potential to become popular and highly upvoted by users.

Figure 4 shows patterns in monthly submissions over time for all “featured” product posts. In Panel (A), each vertical bar represents the total number of monthly submissions from January 2015 to March 2018. Submitted posts are classified into products, podcast episodes, books and games. Rules to featuring podcast episodes, books and games are somewhat different from rules to featuring other products. During some period of time\(^5\), a large number of posts classified as podcast episodes, books or games were systematically featured at a substantially higher rate relative to other products. From October 2014 to January 2017, around 56.6% of all featured posts were one of these three categories.

In the rest of the paper, “featured” products refer to non-podcast-episode, non-book and non-game products, unless otherwise specified. These categories are systematically different from other products, and hence it is natural to exclude them from the set of empirical analyses on startup firms with focused products. Podcast episodes and books are rarely startup firms’ major products, but are instead more often a way to broadcast knowledge and ideas. The company or author associated with games, books and podcasts tend to generate a large amount of similar content, since podcasts have many episodes, book authors write multiple books, and gaming companies release a large number of games.

Panel (B) of Figure 4 shows the monthly share of “featured” products among all products. The share of “featured” products remain stable over time at around a third of all product submissions. The initially spike in share “featured” in 2015Q1 is due to missing data – Product Hunt API seems to have dropped “non-featured” posts in this time period, but data since April 2015 contain the full set of product posts whether “featured” or not. Panel (D) suggests that there does not exist weekly cyclicality in the share of “featured” products. For example, the chance of becoming “featured” is about the same on Tuesdays as on Saturdays, even though twice more products are typically submitted on Tuesdays compared to Saturdays, as evidenced by strong weekly cyclicity in total submissions in Panel (C).

When a product becomes “featured”, it competes for ranking with other “popular” products of the day. Front page ranking depends almost entirely on cumulative authentic Product Hunt user upvotes, and products with the largest number of authentic user upvotes rise to the top of

\[^5\]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.
the daily front page feed.\footnote{An upvote is excluded if Product Hunt internally determines that it is inauthentic or generated by a bot account. Unfortunately, I do not have this information which is only internally available at the company.} Being “featured” gives products the entry ticket to the front page, an important step for the underlying startup firm to acquire attention of potential consumers and investors. Most firms that launch products on Product Hunt emphasize the importance of attaining upvotes, since it is through this channel that products rise to greater visibility and status. A larger number of authentic upvotes increases the product’s chance of becoming “featured”, while also improves the product’s ranking among other “popular” products launched during the same day. A higher ranking increases the likelihood that the product will be noticed by potential consumers, in addition to being a signal about the product’s traction which firms can quote directly to impress investors.

### 2.3 Characteristics of Featured Products

“Featured” products are predominantly technology products. About 92\% of the “featured” products tags the “Tech” topic. Figure 5 shows the most frequent other topics associated with “featured” products excluding “Tech”. These statistics show that over 10\% of “featured” products are in one of the top three most common topics – web apps, iPhone apps, and productivity tools.

Tables 1 and 2 sum up the set of “hunters” of featured products, and the set of upvoting users of featured products respectively. Because the majority of user engagement and product-related activities on Product Hunt occur within “featured” product posts, I provide these descriptive statistics of those users that contribute to these activities by submitting the products and upvoting them.

Table 1 focuses on “hunters” of the 27,141 “featured” product posts submitted between January 2015 and March 2018. Some of these “hunters” have submitted more than one product over time, and hence may be counted more than once in the aggregate statistics. From Table 1, about 30\% of “featured” products have been submitted by one of the product team members. Only 11\% of the “hunters” of featured products are female, fewer than the overall fraction of active female users on Product Hunt. A substantial fraction (about 12\%) of these “featured” products are hunted by employees and early contributors of Product Hunt\footnote{These individuals are identified in a public section of the Product Hunt website listing about 16 current employees and 40 early contributors.}.

Table 2 shows descriptive statistics of users who have upvoted at least one “featured” product between January 2015 and March 2018. These include over 0.5 million unique individuals, and reflect their total amount of activity up to March 2018. Although the average upvoter generates much less activity compared to the average “hunter”, the large size of the user base means that a
large number of users additively contribute to the Product Hunt community in significant ways, and pose a large impact on product rankings through upvoting.

Figure 6 presents aggregate statistics on how upvotes on “featured” products evolve over time. In Panel (A), the distribution of upvotes is drawn spanning every 5 minute bucket within the product launch day. At around midnight, the product has a 20% chance of obtaining an upvote, which gradually increases and peaks at exactly 8AM Pacific Standard Time, before the probability of being upvoted wanes during the rest of the launch day. This graph reflects the amount of user activity on Product Hunt, where users are most likely to browse the website and upvote products at 8AM PST each day. Panel (B) shows the number of upvotes obtained by the number of days that have elapsed since the product launch. The majority of upvotes occur on the launch day, when the product lands the front page, i.e. the daily “popular” feed, and get the largest amount of exposure to users which then convert into upvotes.

To augment the set of product characteristics to acquire a more detailed look into the startup firms that have launched the products, I link Product Hunt posts to company profiles and venture capital funding data obtained through crawling CrunchBase API. Section 2.4 describes the linking process and sample construction, and section 2.5 provides extended descriptive statistics on startup firms in the final sample for empirical analysis.

2.4 Linking to CrunchBase and Sample Construction

To augment product information with data on firms creating the products, I link Product Hunt product posts to company profiles in CrunchBase. This procedure allows me to obtain more detailed characteristics about the startup firms and their founders behind the launched products. CrunchBase is a comprehensive database that maintains up-to-date information on early-stage ventures, investors and events assembled from public sources and validated by moderators. Most companies’ profiles in CrunchBase include their website URLs, which I use to link the company’s CrunchBase profile to its product post on Product Hunt. Also available in CrunchBase data are the startup company’s category group, headquarter location, date founded, profiles of key employees (e.g. founders and management team), as well as information on investors and funding announced.

Linking Product Hunt to CrunchBase entails mapping the URL domain of product link from Product Hunt to company website domain in CrunchBase. Startup firms sometimes change names and website URLs, and these changes are frequently updated in CrunchBase. However, historical product posts on Product Hunt typically contains only the dated product URL. To the extent that historical CrunchBase data snapshots associated with the old product URL are available,
the rate of match success can be improved. I also identify founders and key members of the management team of firms from CrunchBase, and use their individual characteristics such as gender, entrepreneurial experience and employment history to supplement the product-firm level analyses. Other information obtained in CrunchBase API and matched to Product Hunt product posts are also included as additional control variables.

The empirical analyses focus on “featured” products launched on Product Hunt from January 1, 2015 to March 31, 2018, and the unit of analysis is at the product-firm level. Pre-2015 data are excluded from the sample due to the fact that Product Hunt had relatively few users within a year of founding, and mainly relied on a few early key members who contributed to the oldest activities before scaling up to cover a much larger community base and product range. These early data are potentially biased and not representative of overall activities in the technology sector, whereas the later data contain a much larger user base and broader range of submitted startup products.

On average, among products made by startup companies that launched on Product Hunt between January 2015 and March 2018, around 42.1% of “featured” products can be matched to CrunchBase. The match rates are stable across different months, and slowly worsened over time potentially due to the time lag between a company being founded and its entry into the database. In the rest of the subsection, I describe the raw data handling process leading to the final products and linked firms sample for empirical analyses.

First, as previously mentioned in section 2.2, the set of “featured” products for the focus of empirical analyses exclude podcast episodes, books and games for obvious reasons. In addition, I drop non-products such as spams, news articles, infographics, events, surveys and newsletters. Online courses, music and art projects, and political organizations as well as government agencies are also excluded from the sample.

Some product creators host products on third party websites, such as Github and other online platforms where developers share projects and code base. These third-party websites also include Shopify, Instagram, Facebook, and Twitter accounts, through which smaller vendors without their own websites manage an online presence. These instances are dropped from the sample. Additionally, some products are hosted on developers’ personal websites, which are typically these developers’ side projects which have not evolved into independent company identities. These products are excluded as well unless they have separate lone-standing company websites. Similarly, iPhone and Android apps, browser extensions, WordPress plugins, messenger bots without registered company URLs other than those based on the hosting platforms are also excluded.

Some products are made by big software companies that typically create many similar prod-
ucts. In many cases, app developers launch one of their many apps on Product Hunt. These products are also dropped since I cannot measure the relative importance of the launched product compared other products made by the same company but are not launched on Product Hunt, and hence cannot assess the impact of having one successful product on the overall company performance which depends upon many other unobserved products. This exclusion is applicable to superstar firms such as FAGMA (Facebook, Apple, Google, Microsoft, and Amazon) and Twitter, as well as Product Hunt announcements of its own feature updates.

To the remaining products, I link the website URL to CrunchBase to generate product-firm matches and obtain additional information about the startup companies underlying these products. The linking procedure results in a final analysis sample containing over 7,600 matched product-firm pairs in a time period from January 2015 to March 2018. Figure 7 shows the distribution of firm age when a product by the firm is launched on Product Hunt. Firm age is defined by the number of days elapsed since the firm was founded up to the Product Hunt launch. A majority of products in the sample have been launched within four years of founding, and firms are most likely to launch products on Product Hunt about a year after they were founded.

2.5 Sample Summary Statistics

The final sample consists of 7,664 “featured” products launched on Product Hunt between January 2015 and March 2018, each matched to the underlying startup firm which has created the product and is identified in CrunchBase. Figure 3 splits the sample into two groups – the left panel presents statistics on daily top 5 most upvoted products, and the right panel presents statistics on all other (non-top 5) “featured” products. The daily top 5 products are on average 1.6 times more likely to obtain early-stage venture capital funding (i.e. seed, convertible note, and series A) within 6 months following the product launch. While 9.8% of underlying firms of the daily top 5 products are funded, firms of “featured” non-top 5 products are funded at a lower rate of 6.1%.

For about 52% of launched products, the underlying firms’ headquarters are located in the United States. About 16% of the firms are headquartered in Europe. Firms launching daily top-5 products are more likely to be located in Silicon Valley (17%), compared to other firms (13%) launching non top-5 products. The top ranked products tend to be created by younger firms. These products are more likely to be in software and IT sectors, and less likely to be in financial services and healthcare sectors. The average firm behind these products is founded by a team of 2 people. Founders of firms launching daily top-5 products tend to be serial entrepreneurs (rather than first-time founders) and are more likely to be male.

Some of the differences between statistics shown in the both panels potentially result from
characteristics of the product post unrelated to firm fundamentals. For example, the descriptive
information contained in these posts, and the identity of the “hunter” submitting the product
both influence the amount of user attention and eventually number of user upvotes. For example,
“hunters” of daily top-5 products are followed by almost twice as many other Product Hunt users
as the average “hunter” of a non-top 5 product. On average, top-5 products also contain more
descriptive details such as images and videos, and cite more external news articles.

2.6 Data Representativeness

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

Panel (A) of Figure 8 focuses on the total number of firms in the final sample in each category
group defined by CrunchBase, and panel (B) shows the match rates in each category group among
CrunchBase firms founded between 2014 and 2015 and based in the United States and in Europe.

3 Product Rankings and Early-Stage VC Funding

Anecdotal evidence suggest that having a successful product launch on Product Hunt is associated
with higher ability to attract venture capital investments. To measure “success” in the launch, I
use the daily ranking of products on the day of product launch. After a product is submitted to
Product Hunt, it will begin to attract user upvotes. Those products that get initial traction will
be selected by Product Hunt to be “featured” on the daily feed of popular products. Typically,
Product Hunt selects about a third of all submissions on a day to be “featured”, and that this
proportion does not vary systematically across days of the week or over time. Those products
selected for “featuring” will enter the front page to compete for ranking, which is determined
solely by total number of authentic upvotes. 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 early-stage VCs look at information on Product Hunt and use the platform to source deals (Williams, 2014). According to a 2014 Fast Company article, a surge in the number of early-stage startup companies have made Product Hunt useful for investors gathering information on startup products, as a tool to help them “separate the wheat from the chaff” (Melendez, 2014). SV Angel, a prominent seed fund, has closed a deal sourced through Product Hunt with TapTalk—a chat app launched and ranked no. 2 on April 11, 2014 (DeAmicis, 2014). Product information on Product Hunt is updated in a timely manner, which sometimes outpaces even major tech news outlets such as HackerNews. As a convenient tool that can be accessed online from around the world, Product Hunt appeals to venture capitalists particularly for collecting product information on firms located outside Silicon Valley and firms with larger information asymmetry which are potentially more risky investments. In December 2016, AngelList acquired Product Hunt for $20 million. The merger formed a tighter connection between Product Hunt and investors of early-stage companies including angel investors and seed VCs. In fact, several of Product Hunt’s earliest employees and key team members (e.g. Niv Dror and Erik Torenberg) have started their own venture capital firms.

Apart from the fact that early-stage investors directly look to Product Hunt to obtain information about startups’ products, firms that launch a top-ranked product are also more likely to be viewed by a large number of Product Hunt community members who convert into consumers. Developers and product teams have mentioned that traffic to their products’ webpage usually spikes immediately after the product becomes top-ranked on Product Hunt, and that these website visits translate into product sign-ups. In this sense, firms that obtain more upvotes and higher ranks are likely to have better fundamentals after the Product Hunt launch, when these upvotes signal potential consumer demand and are correlated with the firm’s future sales.

Gaining popularity on Product Hunt also implies getting more attention and discussions around the product from the community, which may help the maker team improve the product upon the feedback. Startup founders may take the opportunity of having many users look at their product to solicit feedback on what they have built, what features to change about the product and how to attract more customers. It is also a channel for them to engage with users and explain the product in a more personable way. Product Hunt also organizes offline meetup events, where entrepreneurs can have face-to-face meetings with the community members.

In addition, Product Hunt also has an encouragement effect that spurs innovation in the extensive margin. Many makers create products solely because Product Hunt exists as a channel
that largely increases the chance that their products will gain traction. Product Hunt does not only increase the visibility of existing startup firms, but also leads to more innovative activity, as more startup firms may take shape as a result of the availability of Product Hunt’s service which potentially allows them a chance to succeed.

In many ways, Product Hunt is a bridge between entrepreneurs who have ideas for a new product and more established individuals in the startup community. It facilitates connections from entrepreneurs to both investors and potential customers. The impact of the platform is especially pronounced for firms that may lack resources or established relationships to gain an entry ticket to entrepreneurship and venture capital funding. It helps create a channel for products to gain visibility through a more democratic process than what is typical in the relationship-driven world of entrepreneurship, and picks the winner by popularity within a community instead of existing connections or credentials to directly impress key players such as media and prominent investors.

3.2 Product Visibility and Status: Upvotes and Ranking

To assess the real impact of product traction on Product Hunt, I need to capture a well-defined measure of product visibility. From the investor’s perspective, or the perspective of an outside observer of the platform, the product signals that are immediately visible from the platform are the number of current total upvotes and the relative position of the product (the rank) on a daily basis, for the set of products that are selected to be “featured”. The rank of a product on the daily feed is determined mainly by total number of authentic upvotes on the product, relative to other products “featured” on the same day and the timing of these upvotes. The rank updates in real time to reflect current total activity. The rank does not exactly reflect the order of products according to the total number of upvotes, since some upvotes are not counted toward the ranking if they are detected as fake upvotes by Product Hunt.

I use product rank to be the signal for quantifying information frictions on Product Hunt. There are a few advantages to this approach compared to using the other visible metric – total upvotes. First, the relative position of products on the same day’s feed is a much more salient feature than total upvotes. Top ranked products are much more likely to be viewed by users and to get attention from investors. Also, an observer may easily notice that the ranks do not completely reflect perceived total upvotes, they may already guess that the ranking takes other factors (fake upvotes, for example) into account and would consider rank to be a more convincing certification of potential product demand. As the number and composition of users of Product Hunt change.

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8The researcher does not have access to information on which upvotes are classified as authentic versus fake, which is only available to Product Hunt internal staff.
over time, the raw upvote counts may reflect factors specific to the particular day and to Product Hunt active user composition around the time of the launch. Hence upvotes on days that are a long time apart may not be directly comparable. 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 product traction than unscaled number of total upvotes.

Second, rankings of products permit quantifiable measures of shocks to this metric, which isolate the effect of rankings from other endogenous factors including user upvotes. Since products’ rankings depend on the relative position of products in the context of other products “featured” on the same day, it is easy to isolate shocks to ranking by exogenous factors that change this “context”. Section 4 covers the exogenous variation in relative ranks in more detail and discuss identification strategies for estimating the causal effect of product ranks. The reverse does not hold, as there may not exist a feasible setting in which a shock only affects the number of upvotes but does not change the ranking at all or users’ interpretation of the ranking. Even if (in a hypothetical world), the researcher buys a large number of bots to randomly generate upvotes toward a number of “treated” products, which presumably will be detected by Product Hunt as fake upvotes and do not change the ranking – users observing the combination of ranking and upvotes will immediately infer that the quality of upvotes on the highly upvoted but lower ranked product must be relatively low and hence the treatment does not only affect upvotes, but inevitably also affects users’ perception of the upvotes which will directly affect outcome. Hence this does not allow exogenous separation of the a causal effect of purely upvotes.

3.3 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 less time leading to deal closing, lead investors with a larger number of past deals, 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.

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 causally identifying the effect of product rank on the
underlying firm’s subsequent VC funding probability.

Section 2 has described how Product Hunt rankings are generated. Rankings provide a particularly nice setting for capturing exogenous shocks to the product’s status, since the relative ranking depends not only on the product’s own upvotes, but also its relative position in the context of all other launched products of the day. The rankings are determined by up-do-date authentic user upvotes (excluding those classified as fake upvotes) and timing of these upvotes. Although ranking continues to update based on all present upvotes, the majority of upvoting activity occurs during the launch day, and relative rankings tend to stabilize towards the end of the day. Occasionally, upvotes that sporadically occur after the launch day will flip adjacent products’ ranks.

I do not observe the history or exact product rankings at each point in time. I observe the current ranking of historically launched products, and for products launched a long time (e.g. over a year) ago, this would not reflect the ranking of products when VCs were checking out the products to decide on deals. I also observe the timing of each upvote, but cannot distinguish between upvotes that count as authentic or classified as fake by Product Hunt\(^9\). I construct a “recovered” rank measure that captures the products’ order of total upvotes by the end (11:59PM PST) of the launch day.

There is measurement error in “recovered” rank due to unobserved factors such as spam upvotes, but it should closely track the actual rank after the launch day with some noise. Although I do not observe the actual end-of-launch-day ranks of all products historically, I can retrieve the exact variable for recently launched products. Specifically, I scrape the ranks of products launched only a few weeks prior to the present, and the rank of the scraped products should not differ much from when the launch day ended and the information is likely the same as that observed by early-stage 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 estimate toward zero. The downward bias can be written as

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

where \(\sigma_x^2\) is the variance in the regressor, and \(\sigma_u^2\) is the variance of the measurement error contained in observed noisy version of the regressor. The mis-measured rank can be written as

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

Where \(u \sim N(0, \sigma_u^2)\). For most products, I do not observe the actual end-of-launch-day rank \(R\) since the current ranking updates to reflect total up-to-date upvotes. However, if the amount of

\(^9\)Factors considered to predict spam upvotes are internal information to which I do not have access, which may include IP address of the registered the account, voting rings, and spikes in upvotes concentrated in a short period of time.
random noise in “recovered” product ranks is assumed constant over time, then I can estimate the measurement error by focusing on a subsample of recently launched products. To do so, I obtain the rankings of “featured” products launched in September 2018, which reflects total upvoting activity up to the time the data was scraped on the evening of October 11, 2018. These scraped ranks are taken to be the accurate ranks $R$, and likely observed by early-stage VCs looking at Product Hunt to acquire information about potential investments. Detailed upvote information including timing of the upvotes are collected to calculate the “recovered” rank, i.e. the noisy regressor $\tilde{R}$. Then the measurement error can be estimated as the variance in $\tilde{R} - R$, which is about $5.40$ among “featured” products launched in September 2018. To the extent that this is a usual time period with similar amount of noise in “recovered” ranks compared to historically launched products, this can be taken as an estimate for overall magnitude of $\sigma_u^2$.

The variance of the regressor $R$ is $\sigma_x^2 \approx 72.45$ in the set of September 2018 “featured” products. Combining these estimates, we get that the downward bias in the OLS estimate should be $\gamma = \frac{1}{1+\frac{5.40}{72.45}} \approx 0.93$ due to noise in the measurement of “recovered” product rank.

Another source of bias in the OLS estimate is that there are various unobserved factors that influence both the product’s rank and the underlying startup’s funding outcome. A number of factors determine user upvotes and hence a product’s daily rank, including the day on which it is submitted and hence the set of products to compete with it for rank, and the length of time that Product Hunt allows the product to be on the front page where it gets the most exposure to user views which convert into upvotes. These factors have a mixture of implications for the direction of omitted variable bias in the OLS estimate.

To provide an intuition for the direction of omitted variable bias, I explore whether user upvotes indicate quality or noise of the products. Table 4 shows results from regressing startups funding probability within the next 6 months on measures of product traction among Product Hunt users (i.e. upvotes in the first hour of launching, and upvotes by the end of the launch day). Columns 1 and 2 focus on “featured” products, and columns 3 and 4 focus on products that are not “featured” and hence do not enter the front page to be ranked relative to one another. These results show a contrasting pattern between “featured” (ranked) and “non-featured” (unranked) products. While the funding probability is significantly positively associated with product traction (measured by taking the logarithm of total upvotes) among “featured” and hence ranked products, the association is weakly negative among “non-featured” and hence unranked products. Among products that do not get an entry ticket to the front page to compete for rank, a larger number of upvotes predict a weakly negative change in subsequent venture capital funding probability.
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 on upvoter traction for the “non-featured” products are negative albeit statistically insignificant. It is likely that firms can obtain a few extra upvotes without putting much effort into the product itself or significantly altering firm fundamentals. The firms that are less likely to attract VC funding absent Product Hunt may try harder to gain upvotes, with the knowledge that these upvotes can potentially improve their chance of becoming “featured” and more highly ranked, which may eventually result in an improved chance of being funded.

Another reason that the upvotes can be negatively associated with the ability to attract early-stage VC funding in the absence of a publicity effect is due to an internal feature of Product Hunt. Product Hunt moves the official launch time of some “featured” posts’ to give particular products more time and exposure on the front page where it is most likely to get users’ attention. The decision to move a particular post depends on a few observed factors as well as potentially unobserved factors correlated with the product’s inherent quality and likelihood to obtain venture capital funding.

On average, moved posts are less upvoted without Product Hunt’s help extending their time of high exposure to user views on the front page feed. Table 5 shows coefficients from an OLS regression of whether a post is moved into today’s product feed on the predicted traction of the post. Being moved is associated with less traction among upvoters absent the move. “Predicted traction” of posts are defined by the predicted number of launch day upvotes on the product given only ex-ante characteristics, which exclude information about whether the post was moved and the actual number of launch day upvotes. The specifics to constructing the measure is covered later in this section.

On the other hand, moved posts on average obtain more actual upvotes than posts that are not moved, because they are allowed extra time on the product ranking feed and hence have larger exposure to users, as Table 10 shows. Combining these observations suggests that omitted variables in the OLS regression tends to induce downward bias in the estimate of the effect of product rank. Both mis-measurement in “recovered” ranks and the omission of endogenous characteristics that affect product rank likely lead to an under-estimated OLS effect size.

To provide identification for the effect of product rank on subsequent early-stage VC funding, I use instrumental variable strategies that exploit two separate sources of exogenous variation in product rankings. The intuition behind these instruments relies on the observation that particular
high-impact launched posts shift down the current product’s rank exogenously, without having any relationship to the current product’s fundamentals, when they happen to be “featured” on the same day and dominate users’ attention. These high-impact launches can be used as exogenous shocks to identify the effect of product ranks.

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 Construction of 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
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.

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

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.
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.

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

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 gets 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.\footnote{Note 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.}

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 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, ... , 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 $N(0, \sigma^2_t)$, 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 assumed 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 $p(\theta|\{\eta_t, \sigma^2_t\}_t=0^T) \sim N(\bar{\eta}_T, \bar{\rho}_T^{-1})$. Denote precision $\rho_t$ as the inverse of variances $\rho_t = \sigma_t^{-2}$ of signals in each time period. It is easy to show that these relevant parameters are sufficient statistics calculated from signals in each period.

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

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.

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

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

Another underlying assumption is that the crowd signal \(\tilde{s}\) is equally informative for startup firms with different baseline characteristics (that is, \(\sigma^2_\iota\) 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 \(\rho_T = \bar{\sigma}^{-2}_T\) and \(\rho_\iota = \sigma^{-2}_\iota\).

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

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

(5)

Hence proves the following lemma.

**Lemma 1.** The effect of the crowd signal on investor’s posterior expectation about startup profitability \( E \left[ \theta(\bar{\eta}_T, \bar{\sigma}_T^2) | \bar{s} \right] \) is equal to \( \lambda \), the relative informativeness of the “crowd signal”. When the crowd signal is equally informative across firms, i.e. \( \sigma_i^2 \) is independent of \((\bar{\eta}_T, \bar{\sigma}_T^2)\), the effect of crowd signal on investor’s expectation decreases in the variance \( \bar{\sigma}_T^2 \) of the prior after aggregating ex-ante information.

More intuitively, \( \bar{\sigma}_T^2 \) is a measure of investors’ uncertainty about a startup’s profit potential. Larger uncertainty in the baseline is reflected by larger variance \( \bar{\sigma}_T^2 \) 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

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

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 \( \bar{s} \) is Gaussian \( N(\theta_0 + \Delta, \sigma^2) \) 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 \( \bar{s} \) is

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

(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).

$$y^*(\tilde{s}, \epsilon) = 1 \left( E \left[ \xi \left( \theta(\tilde{\eta}_T, \tilde{\sigma}_T^2) \right) | \tilde{s} \right] - c - \epsilon \sigma_c \geq 0 \right)$$  \(7\)

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

$$E \left[ y^* | \tilde{\eta}_T, \tilde{\sigma}_T^2 \right] = Pr \left( \epsilon \leq \frac{1}{\sigma_c} \left[ E \xi \left( (1 - \lambda)\tilde{\eta}_T + \lambda(\theta_0 + \Delta) \right) + \nu \right] - c \right)$$  \(8\)

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

$$E \left[ y^* | \tilde{\eta}_T, \tilde{\sigma}_T^2 \right] = Pr \left( \epsilon \leq \frac{1}{\sigma_c} \left[ \xi \left( (1 - \lambda)\tilde{\eta}_T + \lambda(\theta_0 + \Delta) \right) + \frac{\xi^2(2) \left( (1 - \lambda)\tilde{\eta}_T + \lambda(\theta_0 + \Delta) \right)}{2\rho^2_s} \right] - c \right)$$  \(9\)

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 $Pr(\epsilon \leq 0) \approx 9\%$, this implies that the calibrated $c \approx 1.3\sigma_{c} + \xi(\bar{\eta}^{*}) + \frac{\xi(2)(\bar{\eta}^{*})}{2\rho_{*}^{2}}$ where $\bar{\eta}^{*} = (1 - \lambda)\bar{\eta}_{T} + \lambda(\theta_{0} + \Delta)$.

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 $EffectSize(\bar{\eta}_{T}, \bar{\sigma}_{T}^{2})$ for a startup with prior information captured by sufficient statistics $(\bar{\eta}_{T}, \bar{\sigma}_{T}^{2})$.

$$EffectSize(\bar{\eta}_{T}, \bar{\sigma}_{T}^{2}) = \frac{\partial E[y^{*}|\bar{\eta}_{T}, \bar{\sigma}_{T}^{2}]}{\partial \Delta} \tag{10}$$

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 $E[\tilde{s}] = \bar{\eta}^{*} > \bar{\eta}_{T}$ always holds for products that becomes “featured”. $EffectSize(\bar{\eta}_{T}, \bar{\sigma}_{T}^{2})$ can be written as

$$EffectSize(\bar{\eta}_{T}, \bar{\sigma}_{T}^{2}) = \frac{\rho_{T}\bar{\eta}_{T} + \rho_{i}(\theta_{0} + \Delta)}{\rho_{T} + \rho_{i}} \phi \left( \frac{1}{\sigma_{c}} \left[ \frac{\xi(1)(\bar{\eta}^{*})}{\rho_{T} + \rho_{i}} + \frac{\xi(3)(\bar{\eta}^{*})}{2(\rho_{T} + \rho_{i})\rho_{*}^{2}} \right] \phi \left( \frac{1}{\sigma_{c}} \left[ \frac{\xi(1)(\bar{\eta}^{*})}{\rho_{T} + \rho_{i}} + \frac{\xi(3)(\bar{\eta}^{*})}{2\rho_{*}^{2}} - c \right] \right) \right) \tag{11}$$

Where $\bar{\eta}^{*} = \frac{\rho_{T}\bar{\eta}_{T} + \rho_{i}(\theta_{0} + \Delta)}{\rho_{T} + \rho_{i}}$.

**Theorem 1.** Assume $\theta + \Delta > \bar{\eta}_{T}$. When $\rho_{T}$ is sufficiently large, $EffectSize(\bar{\eta}_{T}, \bar{\sigma}_{T}^{2})$ 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 $\eta_T$. It is immediate that the effect size of social information
relative to baseline characteristics is exactly equal to the ratio $\kappa = \frac{\rho}{\rho_T}$.

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

$$EffectSize(\eta_T, \rho_T) \approx \frac{0.17\kappa}{(1 + \kappa)\sigma_c}$$

### 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 $\Delta = \beta_0 + \beta_1 \eta_T + \epsilon_\Delta$. 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 $s = \theta_0 + \Delta$. 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 targetting. 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


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

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

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>
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<th>SD</th>
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<th>p75</th>
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Notes: Table shows summary statistics of active 2018 users on the Product Hunt platform.
Table 2: Summary Statistics on Upvoters of Featured Products (2015Q1 – 2018Q1)

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Notes: Table shows summary statistics of active 2018 users on the Product Hunt platform.

Table 3: Summary Statistics of Regression Sample

<table>
<thead>
<tr>
<th></th>
<th>Daily Top 5 (N = 1583)</th>
<th>Other Featured (N = 6081)</th>
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<tbody>
<tr>
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<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Seed VC Funding</td>
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<td></td>
</tr>
<tr>
<td>Within 6 Months (% Yes)</td>
<td>9.73</td>
<td>29.64</td>
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<tr>
<td>Firm Location</td>
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<td></td>
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<tr>
<td>US</td>
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<td>0.50</td>
</tr>
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<td>Europe</td>
<td>0.18</td>
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<td>VC Hub</td>
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<td>SF Bay Area</td>
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<td>Firm &amp; Founder Characteristics</td>
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<td></td>
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<tr>
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<td>Healthcare</td>
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<tr>
<td>Moved into Today</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

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<tr>
<th></th>
<th>Obtain Early-Stage Funding within 6 Months</th>
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<th></th>
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</thead>
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<tr>
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<td>Non-Featured</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</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 cyclicality 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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<tbody>
<tr>
<td>-0.237***</td>
<td>-0.217***</td>
<td>-0.216***</td>
<td></td>
</tr>
<tr>
<td>(0.065)</td>
<td>(0.065)</td>
<td>(0.066)</td>
<td></td>
</tr>
</tbody>
</table>

Controls: Weekly Cyclicality
- Y Y Y

Controls: Firm Characteristics
- N Y Y

Controls: Founder Characteristics
- N N Y

Fixed Effects
- Year-Month

Sample
- All

Number of Observations
- 7664

R²
- 0.107

Fraction Moved
- 0.265

Mean Predicted Traction
- 0.143

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 cyclicity 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</th>
<th>IV/2SLS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Product Daily Rank</td>
<td>0.0018***</td>
<td>0.0063*</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0032)</td>
</tr>
<tr>
<td>Traction Weighted Moved Posts</td>
<td>-1.7877*** (0.2784)</td>
<td>-1.9809*** (0.2553)</td>
</tr>
<tr>
<td>Controls: Weekly Cyclicity</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Post Characteristics</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Controls: Firm Characteristics</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Controls: Founder Characteristics</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year-Month</td>
<td>Year-Month</td>
</tr>
<tr>
<td>Sample</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>7664</td>
<td>7664</td>
</tr>
<tr>
<td>Mean Outcome</td>
<td>0.068</td>
<td>0.068</td>
</tr>
<tr>
<td>Median Rank</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>R²</td>
<td>0.033</td>
<td>0.003</td>
</tr>
<tr>
<td>First Stage F-Statistic</td>
<td>94.252</td>
<td>79.340</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 cyclicity 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>Funded Before</th>
<th>Median Rank</th>
<th>St Dev Rank</th>
<th>No. Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm ( N = 7629 )</td>
<td>Not in VC Hub</td>
<td>5.8%</td>
<td>25.7%</td>
<td>13</td>
<td>11.1</td>
</tr>
<tr>
<td></td>
<td>In VC Hub</td>
<td>10.0%</td>
<td>54.7%</td>
<td>13</td>
<td>11.0</td>
</tr>
<tr>
<td>Founder ( N = 4885 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Not Serial Entrepreneur</td>
<td>10.0%</td>
<td>44.3%</td>
<td>13</td>
<td>10.9</td>
</tr>
<tr>
<td></td>
<td>Serial Entrepreneur</td>
<td>8.6%</td>
<td>46.7%</td>
<td>11</td>
<td>10.4</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>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS (1)</td>
</tr>
<tr>
<td>Not Serial Entrepreneur</td>
<td>0.0023***</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
</tr>
<tr>
<td>Serial Entrepreneur</td>
<td>0.0016***</td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
</tr>
<tr>
<td>Controls: Weekly Cyclicality</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Post Characteristics</td>
<td>N</td>
</tr>
<tr>
<td>Controls: Firm &amp; Founder Characteristics</td>
<td>N</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year-Month</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>4909</td>
</tr>
<tr>
<td>Mean Outcome</td>
<td>0.095</td>
</tr>
<tr>
<td>R²</td>
<td>0.033</td>
</tr>
<tr>
<td>First Stage F-Statistic</td>
<td>8.768</td>
</tr>
<tr>
<td></td>
<td>4.208</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>Obtained Early-Stage Funding within 6 Months</th>
<th>OLS (1)</th>
<th>IV/2SLS : Main Intrument (2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<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>
</tbody>
</table>

- Controls: Weekly Cyclicality
  - Y
  - Y
  - Y

- Controls: Post Characteristics
  - N
  - N
  - Y

- Controls: Firm & Founder Characteristics
  - N
  - N
  - Y

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Year-Month</th>
<th>Year-Month</th>
<th>Year-Month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Observations</td>
<td>7661</td>
<td>7661</td>
<td>7661</td>
</tr>
<tr>
<td>Mean Outcome</td>
<td>0.068</td>
<td>0.068</td>
<td>0.068</td>
</tr>
<tr>
<td>R^2</td>
<td>0.032</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>First Stage F-Statistic</td>
<td>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>Is Moved</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>Traction Weighted Moved Posts</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>
</tbody>
</table>

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

**Fixed Effects:**
- Year-Month: All
- Number of Observations: 7664
- \( R^2 \): 0.156, 0.240, 0.272, 0.280
- Average Upvotes: 140.011, 140.011, 140.011, 140.011
- Fraction Moved: 0.265, 0.265, 0.265, 0.265
- Average Instrument: 1.156, 1.156, 1.156, 1.156
- SD Instrument: 0.864, 0.864, 0.864, 0.864

**Notes:**
- The 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). 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 11: Relationship Between Instrument and Predicted Upvotes

<table>
<thead>
<tr>
<th></th>
<th>Predicted Launch Day End Upvotes</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Traction Weighted Moved Posts</td>
<td>5.075 (3.293)</td>
<td>4.318 (3.316)</td>
<td>4.223 (3.384)</td>
<td>4.390 (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></th>
<th>Characteristics of Startup Company Prior to Product Hunt Launch</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Previously Backed by Early Stage VC</td>
<td>Firm Age ( # Months )</td>
<td>Headquarter in a VC Hub</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>Is Moved</td>
<td>-0.030**</td>
<td>-0.004</td>
<td>-1.828</td>
<td>-0.938</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.010)</td>
<td>(1.218)</td>
<td>(1.154)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Traction Weighted Moved Posts</td>
<td>0.000</td>
<td>0.004</td>
<td>0.295</td>
<td>0.342</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.008)</td>
<td>(0.860)</td>
<td>(0.838)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Controls: Weekly Cyclicality</td>
<td>Y</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>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Controls: Firm Characteristics</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Controls: Founder Characteristics</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Year-Month</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>
<td>All</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>7664</td>
<td>7664</td>
<td>6407</td>
<td>6407</td>
<td>7661</td>
</tr>
<tr>
<td>R²</td>
<td>0.043</td>
<td>0.359</td>
<td>0.017</td>
<td>0.160</td>
<td>0.016</td>
</tr>
<tr>
<td>Average Outcome Variable</td>
<td>0.328</td>
<td>0.328</td>
<td>32.344</td>
<td>32.344</td>
<td>0.247</td>
</tr>
<tr>
<td>Fraction Moved</td>
<td>0.265</td>
<td>0.265</td>
<td>0.270</td>
<td>0.270</td>
<td>0.265</td>
</tr>
<tr>
<td>Average Instrument</td>
<td>1.156</td>
<td>1.156</td>
<td>1.216</td>
<td>1.216</td>
<td>1.156</td>
</tr>
<tr>
<td>SD Instrument</td>
<td>0.864</td>
<td>0.864</td>
<td>0.858</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. Columns 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></th>
<th>Funding Probability (%)</th>
<th>Log (Funding Amount) x 100</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treatment</td>
<td>Placebo</td>
</tr>
<tr>
<td>Founded After 2014</td>
<td>9.60***</td>
<td>-0.63</td>
</tr>
<tr>
<td></td>
<td>(3.39)</td>
<td>(0.73)</td>
</tr>
<tr>
<td>Fixed Effects: Founder</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Controls: Firm Category + Location</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1085</td>
<td>8210</td>
</tr>
<tr>
<td>Number of Unique Founders</td>
<td>501</td>
<td>3684</td>
</tr>
<tr>
<td>R²</td>
<td>0.60</td>
<td>0.78</td>
</tr>
<tr>
<td>Mean Outcome</td>
<td>38.06</td>
<td>85.02</td>
</tr>
<tr>
<td>Mean Regressor</td>
<td>0.49</td>
<td>0.66</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 $\xi^{(k)}(\bar{\eta}^*)$ is well-defined and bounded for all $k \leq 4$, and $\xi^{(k)}(\bar{\eta}^*)$ is strictly positive for each $k \in \{0, 1\}$, and $\xi^{(2)}(\bar{\eta}^*)$ is either strictly positive or strictly negative.

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

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

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

Since $\xi(\cdot)$ is either strictly concave or strictly convex on $[\bar{\eta}_T, s^*]$, 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 $[\bar{\eta}_T, s^*]$, and that it is bounded. Hence we can write $\xi^{(2)}(\bar{\eta}^*) \in [\alpha_2, \alpha_2]$ where $\alpha_2 > 0$. And $\alpha_2$ and $\alpha_2$ are both negative (if $\xi(\cdot)$ is strictly concave) or both negative (if $\xi(\cdot)$ is strictly convex).

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

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

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

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

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

\[
(\rho_T + \rho_i)^2 > R_k(\epsilon)^2 = \frac{\max_{\eta \in \eta_T, s^*} |\xi^{(k+2)}(\eta)|}{2(1 - \epsilon) \Omega_k} \geq \frac{|\xi^{(k+2)}(\tilde{\eta}^*)|}{2(1 - \epsilon) |\xi^{(k)}(\tilde{\eta}^*)|}
\]

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

\[
R_2(\epsilon) = \sqrt{\frac{\min_{\eta \in [\eta_T, s^*]} |\xi^{(4)}(\eta)|}{2(1 - \epsilon) \max \{|\alpha_2|, |\bar{\alpha}_2|\}}}
\]

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

\[
r_0 = \frac{\rho_i(s^* - \tilde{\eta}_T) \max_{\eta \in [\eta_T, s^*]} |\xi^{(2)}(\eta)|}{\Omega_1}
\]

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

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

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

- \( \frac{\partial M_0(\tilde{\eta}^*)}{\partial \rho_T} \) 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.
• For $k \in \{0, 1\}$, any small $\epsilon > 0, \delta > 0$. Define $\delta_0 = \frac{(\rho_T + \rho_i)^\delta}{\rho_i (s^* - \bar{\eta}_T)^{\delta + k}}$, $M = \min \{M_{k+2}(\bar{\eta}^*), M_{k+3}(\bar{\eta}^*)\}$ and $\epsilon_0 = \frac{\epsilon M + 2\delta_0 (1-\epsilon)}{M + 2\delta_0 (1-\epsilon)}$. Then whenever $\rho_T + \rho_i > R_k(\epsilon_0)$, we have

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

Proof. Write $M_k(\bar{\eta}^*) = \frac{\epsilon(k)(\bar{\eta}^*)}{(\rho_T + \rho_i)^2}$ and \(\frac{\partial \bar{\eta}^*}{\partial \rho_T} = \frac{\rho_i (\bar{\eta}^* - s^*)}{(\rho_T + \rho_i)^2}\). Hence for $k \in \{0, 1\}$, we can derive

\[
\frac{\partial M_k(\bar{\eta}^*)}{\partial \rho_T} = -\frac{1}{\rho_T + \rho_i} (\rho_i (s^* - \bar{\eta}_T) M_{k+1}(\bar{\eta}^*) + k M_k(\bar{\eta}^*))
\]

(15)

By Lemma 4, $M_1(\bar{\eta}^*)$ is strictly positive. Since $s^* - \bar{\eta}_T > 0$, $\rho_T > 0$ and $\rho_i > 0$, it follows that $\frac{\partial M_0(\bar{\eta}^*)}{\partial \rho_T}$ is strictly negative. When $\rho_T + \rho_i > r_0$, we have that $M_1(\bar{\eta}^*) + \rho_i (s^* - \bar{\eta}_T) M_2(\bar{\eta}^*) > \rho_i (s^* - \bar{\eta}_T) [M_2(\bar{\eta}^*) - M_2(\bar{\eta}^*)] \geq 0$. Hence $\frac{\partial M_1(\bar{\eta}^*)}{\partial \rho_T}$ is strictly negative.

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

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

(16)

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

(17)

Hence

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

(18)

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

(19)

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

(20)

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

(21)

Therefore,

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

(22)

\[\square\]

**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
\[
\begin{align*}
\text{EffectSize}(\bar{\eta}_T, \bar{s}^2_T) &= \frac{\rho}{\sigma_c} \left[ \frac{\xi^{(1)}(\bar{\eta}^*)}{\rho_T + \rho_i} + \frac{\xi^{(3)}(\bar{\eta}^*)}{2(\rho_T + \rho_i)} \right] \phi \left( \frac{1}{\sigma_c} \left[ \frac{\xi(\bar{\eta}^*) + \xi^{(2)}(\bar{\eta}^*)}{2\rho_i} - c \right] \right) \\
(23)
\end{align*}
\]

Where \( \phi(\cdot) \) is the probability density function of a standard normal variable \( z \sim N(0,1) \). Write \( \bar{\eta}^* = \frac{\rho_r \bar{\eta}_T + \rho_0(\theta_0 + \Delta)}{\rho_T + \rho_i} \) and \( M_k(\bar{\eta}^*) = \frac{\xi^{(k)}(\bar{\eta}^*)}{\rho_T + \rho_i} \). Also define \( \epsilon(\rho_T) = 1 - \left( \frac{\rho_r}{\rho_T + \rho_i} \right)^2 \in (0,1) \). Note that \( \epsilon'(\rho_T) < 0 \) and \( \frac{\epsilon'(\rho_T)}{2(1-\epsilon(\rho_T))^2} = -\frac{\rho^2 \rho_i^2 - \rho_r^2}{\rho_T + \rho_i} \) which decreases in \( \rho_T \) and shrinks to 0 when \( \rho_T \to \infty \). Hence \( \forall \delta > 0 \), there exists \( Q(\delta) = \max \left\{ 0, \frac{(1+\sqrt{1+4\rho^2\rho_i^2-\rho_r^2})}{2\rho_i} - \rho_i \right\} \) such that whenever \( \rho_T > Q(\delta) \), we have \( \left| \frac{\epsilon'(\rho_T)}{2(1-\epsilon(\rho_T))^2} \right| < \delta \). Then

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

Consider the comparative static

\[
\begin{align*}
\frac{\partial \text{EffectSize}(\bar{\eta}_T, \rho_T)}{\partial \rho_T} &= \frac{\rho_c}{\sigma_c} \phi \left( \frac{1}{\sigma_c} \left[ M_0(\bar{\eta}^*) + \frac{M_2(\bar{\eta}^*)}{2(1-\epsilon(\rho_T))} - c \right] \right) \left( M_1(\bar{\eta}^*) + \frac{M_3(\bar{\eta}^*)}{2(1-\epsilon(\rho_T))} \right) \left( c - M_0(\bar{\eta}^*) - \frac{M_2(\bar{\eta}^*)}{2(1-\epsilon(\rho_T))} \right) \\
&\quad - \frac{\partial M_1(\bar{\eta}^*)}{\partial \rho_T} + \frac{\partial M_3(\bar{\eta}^*)}{\partial (1-\epsilon(\rho_T))} \frac{M_0(\bar{\eta}^*) \epsilon'(\rho_T)}{2(1-\epsilon(\rho_T))^2} - \frac{\partial M_3(\bar{\eta}^*)}{\partial (1-\epsilon(\rho_T))} \frac{M_0(\bar{\eta}^*) \epsilon'(\rho_T)}{2(1-\epsilon(\rho_T))^2} + \frac{\partial M_2(\bar{\eta}^*)}{\sigma_c} \left( c - M_0(\bar{\eta}^*) - \frac{M_2(\bar{\eta}^*)}{2(1-\epsilon(\rho_T))} \right) \\
(25)
\end{align*}
\]

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 \( \delta_0 = \frac{(\rho_T + \rho_i)\delta}{\rho_i(s^2 - \bar{\eta}) + 1} \) 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 \( \rho_T > R_k(\epsilon_0) - \rho_i \), we have that for \( k \in \{0,1\} \),

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

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

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

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

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

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 \( \rho_T > 0 \).

\[
\square
\]

A1 Appendix Tables

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

<table>
<thead>
<tr>
<th>Year of Training Data</th>
<th>(1) 2013 - 2014</th>
<th>(2) 2015</th>
<th>(3) 2016</th>
<th>(4) 2017</th>
</tr>
</thead>
<tbody>
<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>
</tr>
<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>
<td>0.000</td>
<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>
<td>0.000</td>
<td>0.421</td>
<td>0.211</td>
<td>0.074</td>
</tr>
<tr>
<td>Tagline Length (Words)</td>
<td>0.018</td>
<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>
</tr>
<tr>
<td>Number of Observations</td>
<td>12235</td>
<td>31576</td>
<td>39531</td>
<td>28882</td>
</tr>
<tr>
<td>Outcome Average</td>
<td>30.519</td>
<td>34.180</td>
<td>33.603</td>
<td>50.494</td>
</tr>
<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>OLS (1)</th>
<th>OLS (2)</th>
<th>OLS (3)</th>
<th>OLS (4)</th>
<th>OLS (5)</th>
<th>IV/2SLS (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Daily Rank</td>
<td>0.0018***</td>
<td>0.0111*</td>
<td>0.0109**</td>
<td>0.0113**</td>
<td>0.0118**</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>
</tr>
</tbody>
</table>

First Stage Dependent Variable: Product Daily Rank

| Controls: Weekly Cyclicality | Y | Y | Y | Y | Y |
| Controls: Post Characteristics | N | N | Y | Y | Y |
| Controls: Firm Characteristics | N | N | N | Y | Y |
| Controls: Founder Characteristics | N | N | N | N | Y |

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 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 A3: No Effect of Product Rank on Venture Rounds 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>
<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>-0.0001</td>
<td>0.0004</td>
<td>0.0006</td>
<td>0.0000</td>
<td>-0.0002</td>
<td>0.0067</td>
<td>-0.0002</td>
<td>0.0067</td>
<td></td>
<td></td>
<td></td>
<td></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>
<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>OLS (1)</th>
<th>OLS (2)</th>
<th>OLS (3)</th>
<th>OLS (4)</th>
<th>OLS (5)</th>
<th>OLS (6)</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></td>
<td>-1.7877***</td>
<td>-1.9809***</td>
<td>-2.0107***</td>
<td>-1.9952***</td>
<td>-3.8471***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2784)</td>
<td>(0.2553)</td>
<td>(0.2543)</td>
<td>(0.2566)</td>
<td>(0.6660)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 cyclicity 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.