Initial Public Offering and New Business Formation:

The Role of Public Firm Disclosures*

John M. Barrios
Washington University in St. Louis & NBER

Jung Ho Choi
Stanford University

Yael V. Hochberg
Rice University & NBER

Jinhwan Kim
Stanford University

Miao Liu
Boston College

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We investigate the potential spillovers of local initial public offerings (IPOs) on local new business formation. New IPOs are associated with a 4% to 10% increase in new business registrations in the public company's geographic area. These effects are magnified in counties with more uncertain economic conditions. Consistent with an information channel, new business registrations positively relate to Edgar downloads of IPO firm public disclosures, and increased download activity further magnifies the effect. Our findings are consistent with public firm disclosures by IPO firms providing information that facilitates new business formation. Additionally, we find similar effects for a financing channel, furthering our inferences as to the positive spillovers from IPOs. Finally, we show that the consumption of IPO firm public disclosures is further associated with entrepreneurial success.

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Corresponding Author: John Barrios (john.barrios@wustl.edu).

I. INTRODUCTION

The study of initial public offerings (IPOs) and their effects on the IPO firm's business and practices has grown considerably in the last four decades. This extensive literature has documented several consequences of going public, including a reduction in the IPO firm's innovative output, (Bernstein, 2015), mergers and acquisitions (Celikyurt et al., 2010), and hiring (Borisov et al., 2022). In recent years, researchers have expanded their scope to begin exploring the spillover effect of IPO activities on the real economy, the labor force, and other firms (see, e.g., Lowry and Schwert, 2002; Benveniste et al., 2003; Butler et al., 2019; Babina et al., 2020; Aghamola and Thakor, 2020; Cornaggia et al., 2022). This paper explores a new dimension of potential IPO spillovers: local new business formation.

Studying the spillover effect of IPOs on new business formation is of first-order interest. First, new business formation is considered a critical driver of economic development (Haltiwanger et al., 2013). Studies using U.S. Census data show that new firms disproportionately drive job growth (Davis and Haltiwanger 1992; Davis et al. 1998; Haltiwanger, Jarmin, and Miranda 2012; Decker et al. 2014; Fairlie, Miranda, and Zolas 2019). At the same time, population-level indices such as the Business Dynamics Statistics Database suggest a secular decline in the rate of business dynamism and new firm formation overall (Decker et al., 2016; Hathaway & Litan, 2014). Understanding what drives the process of new business formation is thus of critical importance. Second, newly listed firms disclose significant amounts of information, such as their business strategy, financial performance, expected future outlook, current, and future investment outlays, material contracts, and business risks. Moreover, information intermediaries that cover public firms—such as financial analysts and the business press—analyze, discuss, and disseminate firms' disclosures. Collectively, these disclosure activities can improve the information environment within publicly-traded firms' industry vertical and geographical area, reducing uncertainty regarding demand, supply, and cost conditions (Mitchell and Mulherin, 1996; Admati and Peiderer, 2000; Badertscher et al., 2013).

Importantly, entrepreneurs must work to discover profit opportunities to launch a successful and sustainable business. Opportunities may exist on the output side of production, the input side, or both, and the existence of such opportunities may lead to the creation of new firms. Much of this entrepreneurial process involves seeking and interpreting information. As a result, gathering information for decision-making is a critical activity for the would-be entrepreneur, playing a first-order role in the decision to establish a new firm. Ryans (2017) shows that the most downloaded corporate filings are the S-1 filings from IPOs—even more so than 10-Ks, 10-Qs, and 8-Ks. This is a testament to the importance of IPO-related disclosures as a source of information to the public, and by extension, to potential entrepreneurs.

We hypothesize that the information in new IPO firm disclosures reduces uncertainty regarding future returns to entrepreneurial activities, thus increasing entrepreneurial entry following IPO events. This effect should be more substantial the closer the geographic proximity to the public firms, as the transmission of soft information serves to augment and add color to the publicly transmitted information in the disclosures, and such transmission likely declines with distance (Liberti and Petersen, 2019).

We empirically examine this hypothesis by utilizing geographic variation in IPOs over U.S. counties and time. We capture new business starts by employing a novel dataset of the complete census of new for-profit business registrations in the United States with zip code and county-level information provided by the Startup Cartography Project (SCP). We employ a difference-in-differences (D.D.) design to compare new business registrations in counties where an IPO has been initiated to those in counties that have not experienced a recent IPO, before and after the occurrence of the IPO. Our D.D. specification includes a vector of time-varying county characteristics (population, income per capita, and the number of public firms) as well as county and quarter-year fixed effects.

Because IPOs may not be exogenous to new business formation, we utilize the identification approach employed in Bernstein (2015), which instruments for IPO completions using the returns on the NASDAQ index in the months immediately following a firm's filing for IPO. We find that post-IPO county-quarters observe a 4 to 10% increase in new business registrations relative to county-quarters in which there were no recent IPOs. This translates into 5-12 new business registrations a quarter, on average, after the IPO. We then explore whether an IPO event may lead individuals to consider the possibility of launching a business, even if they do not eventually choose to launch one. To do so, we measure entrepreneurial interest (expression of interest in entrepreneurship) using google searches for terms related to entrepreneurship, such as "how to start a business" or "how to incorporate" (Barrios et al., 2020). Consistent with our prior findings, the D.D. specification documents an approximate 16.2% increase in search share for entrepreneurship and new business formation terms after an IPO. Finally, we use the same methodology to show an increase in financing for new businesses. Specifically, we find that both the number and dollar volume of SBA loans to newly formed companies increase in the county following an IPO event. Similarly, we find that the number of venture capital deals and the dollar volume of VC investment in the county increase after a local IPO.

An obvious concern is that omitted factors such as local economic growth in the area may jointly determine IPO activity and new business formation. Prior research shows that IPOs do not necessarily lead to, and can sometimes hurt, local economic growth (Cornaggia et al., 2022). We first assuage this concern by looking at the parallel trends assumption; we find evidence of parallel trends, which alleviates concerns that differential patterns in growth are driving our results. Furthermore, we find that neither contemporaneous wages nor employment appear to rise in the local region following an IPO. If economic growth does not explain the increased new business formation after local IPOs, could information disclosed by IPO firms spilling over to local entrepreneurs cause the effect?

Our hypothesis argues that the relationship between IPOs and new business formation is a result of the IPO's informational role in reducing uncertainty. If new information from IPO firms is the driver underlying our findings, we would thus expect our results to be concentrated in situations where economic uncertainty is the highest ex-ante. Consistent with these arguments, we find that the positive link between IPO and local entrepreneurship is more pronounced in locations where economic uncertainty, measured by volatility of wage growth, is high.

Next, we further validate the information story by examining how the volume of Edgar downloads of public firm reporting changes around new IPOs, and how these downloads relate to new business registrations. A significant implied relation of the information acquisition hypothesis is that we should expect more intense information acquisition patterns following the IPO event. We show that consumption of information, as measured by downloads of public filings from Edgar, is higher in counties that experience an IPO, and that new business registrations are higher in counties that are actively downloading filings. Moreover, we find that the positive relationship between an IPO and new business formation is magnified in counties with high levels of S-1 downloads. These tests corroborate the inference that the positive link between IPO and new business registrations is driven by more public disclosures available to potential entrepreneurs.

Third, to further corroborate that our results are driven by information provision to entrepreneurs, we consider cases when an IPO is likely to provide more information versus less. Specifically, we separate IPOs into spinoffs from public firms versus private-to-public IPOs. This comparison is based on the view that the production of new information is likely more prevalent when a private firm goes public than when a subsidiary is spun off, as the parent company already reported public information on the subsidiary before the IPO. Consistent with our hypothesized information mechanism, we see that the increase in new firm registrations is concentrated around private-to-public IPOs.

Collectively, the above analyses validate an information-based effect of IPOs on entrepreneurial activity and raise the bar for an alternative channel to explain our results. While our findings do not preclude a role for other mechanisms, they provide strong support for a disclosure mechanism in the relationship between IPOs and new business formation.

Finally, while more exploratory in spirit, we examine the evidence as to whether information spillovers from IPO firms impact start-up operation efficiency and local business dynamism. Specifically, we find that start-ups that actively consume public firm information are 27% and 13% more likely to have an IPO or be acquired, respectively, than those that do not do so. Moreover, higher market entry in the last period is associated with more market exit. More importantly, this business dynamism is more active after IPOs, consistent with the notion that economic uncertainty hinders firms' continual creation and destruction (Bloom, 2009) and that a better information environment brought by IPOs alleviates the impact of uncertainty.

This paper makes several contributions to the literature. First, our work contributes to the extensive existing literature on initial public offerings, and in particular, IPO spillovers (see, e.g., Lowry and Schwert, 2002; Benveniste et al., 2003; Babina et al., 2020; Cornaggia et al., 2018; Butler et al., 2019; Aghamola and Thakor, 2020). While we focus on the role of information in spillovers to new business formation, a key contribution of our findings to this literature is providing new, causal evidence on spillovers of IPOs to entrepreneurial activity. In this regard, our paper also speaks to the literature on entrepreneurship and new business formation. Our findings provide a first insight into the process through which potential entrepreneurs obtain relevant information when deciding to launch a new venture.

Second, our paper adds to the literature on the externalities from public firm disclosures (Durnev and Mangen, 2009; Beatty et al., 2013; Badertscher et al., 2013; Shroff et al., 2014; Bernard et al., 2020). For example, Badertscher, Shroff, and White (2013) show that private firms are more responsive to their investment opportunities when they operate in industries with greater public firm presence. Durnev and Mangen (2009) show that accounting restatements are associated with lower abnormal returns and reduced investment by non-restating firms in the industry. The authors suggest a "learning" effect in that restatements convey information about investment projects to the managers of restating firms' competitors. Breuer (2021b) finds that European mandatory financial reporting regulations facilitate product market competition. While these studies primarily focus on the intensive margin effects of disclosure spillovers—the investment decisions of established firms, our study contributes to this literature by using IPOs and the broader entrepreneurial setting of new business formation to show that public firm disclosures' positive externalities also affect the extensive margin of new business formation. Our setting and the mechanisms examined allow us to provide a more holistic understanding of how information spillovers from public firms may spur entrepreneurial activity and new firm formation.

Along the prior line or reasoning, our paper also contributes to the debate on the cost and benefits of disclosure regulation. Despite its pervasiveness, disclosure regulation is often quite challenging to justify because of market-based incentives to disclose information (Admati and Pfleiderer, 2000; Leuz and Wysocki, 2016; Berger, 2011). That is, since the firm ultimately bears the costs of obfuscating information, the firm has incentives to disclose information to reduce such costs (e.g., Admati and Pfleiderer, 2000). One justification put forward in favor of mandatory disclosure is the presence of positive externalities to such disclosure (e.g., Breuer et al., 2020; Kim and Valentine, 2021; Kim and Valentine, 2022). Our paper provides additional evidence consistent with corporate disclosures' positive externalities, namely, spurring new business formation.

II. DATA SOURCES AND KEY VARIABLES

In this section, we describe our variables and the various databases used to construct them. Overall, our sample is comprised of 359,892 county-quarter observations. When data is available, we also conduct tests at the county-industry-quarter level, with a sample comprised of 866,359 county-industry-quarters in additional tests further described below.

A. *Initial Public Offerings*

Our main proxy for the availability of public disclosures relevant for entrepreneurs is *Post IPO*¸ defined as a county-specific indicator variable that equals to one for every county-quarters after the IPO quarter, and zero otherwise.[1] Our motivation for this proxy stems from the fact that IPOs represent a significant expansion in public information available to the public through mandated corporate filings, newspaper coverages, and analyst reports, all of which provide relevant information for would-be entrepreneurs. For example, Ryans (2017) shows that the most downloaded corporate filings are the S-1 filings from IPOs—even more so than 10-Ks, 10-Qs, and 8-Ks. This is a testament to the importance of IPO-related disclosures as a source of information to the public, and by extension to potential entrepreneurs.

We include counties that never had an IPO in our sample. These serve as a benchmark comparison group and have the variable $Post\ IPO$ set to zero over the entire sample period. We collect IPO issuance data using Thomson Financial's SDC New Issues database. The sample starts from 1988 Q1 and ends in 2016 Q4. The data contains county as well as industry information at the 2-digit SIC level for each IPO, which we exploit in certain model specifications described further below. Following the IPO literature, we exclude IPO filings of financial firms (SIC codes between 6000 and 6999), unit offerings, closed-end funds (including REITs), ADRs, limited partnerships, special acquisition vehicles, and spinoffs. We identify 7,892 IPOs over the sample period of 1988 to 2016. In Figure 1, we plot the geographic variation in IPOs among U.S. counties. We observe variation across geography and time with regards to IPO activity.

B. Business Formation Measures

[1] In additional tests, we use *Public Firm Presence*, defined as the proportion of public firms in each NAICS 3-digit industry-year, following Badertscher et al. (2013) and Shroff et al. (2017) as an alternative proxy for the availability of public disclosures relevant for entrepreneurs.

We utilize two complementary measures of entrepreneurial activity, which serve as our dependent variable of interest.

II.B.1. Business Registrations

Our first measure of new business formation uses new business registrations. Our business registration data is obtained at the county level from the Startup Cartography Project (SCP) database. The SCP leverages business registration records, which are public records created when an individual registers a new business as a corporation, LLC, or partnership. Importantly, as noted by Guzman and Stern (2019), while it is possible to found a new business without business registration (e.g., a sole proprietorship), the benefits of registration are substantial, and include limited liability, various tax benefits, the ability to issue and trade ownership shares, and credibility with potential customers. Business registrations reflect the population of incorporated businesses operating in a location (which may differ from their state of incorporation) that have taken on a form that is a pre-requisite for growth or employment. We define our main variable of interest, $Log(1 + New\ Business\ Reg)$, as the natural logarithm of one plus the number of new business registrations in the county in the period of interest.

The SCP business registration data covers 50 states from 1988 to 2014 and 47 after 2014 (IL, SC, and MI drop out of the sample after 2014). The SCP data is available at various levels of geographic aggregation (we use county level), however, the data does not allow for identification of the firms' industry. All in all, $Log(1 + New\ Business\ Reg)$ complements $Log(1 + Establishment\ Birth)$ by providing a more refined measure of new business formation. Specifically, $Log(1 + New\ Business\ Reg)$ avoids the limitation of the establishment birth measure, which may be driven by new branches of existing companies rather than new business formation. We graph the county variation of $New\ Business\ Reg$ in Figure 2.

II.B.2. Establishment Births and Deaths

Our second measure comes from the U.S. Census Statistics of U.S. Business database (SUSB), which covers all U.S. business establishments with paid employees spanning the years 2000 to 2015. The data source provides information on new establishment births at the county level at the 2-digit NAICS level. The SUSB defines an establishment birth as establishments that have zero employment in the first quarter of the initial year and positive employment in the first quarter of the subsequent year. We define $Log(1 + Establishment\ Birth)$ as the natural logarithm of one plus the number of new establishment formations, measured at the county and 2-digit NAICS level. Moreover, the SUSB data offers a unique opportunity to examine establishment deaths, which we utilize to assess the dynamics of county-level entrepreneurial activity. That is, in later tests described further below, we examine whether new establishment formations induced by local IPO activity leads to higher level of eventual deaths. Establishment deaths are defined as establishments that have positive employment in the first quarter of the initial year and zero employment in the first quarter of the subsequent year. We define $Log(1 + Establishment\ Death)$ as the natural logarithm of one plus the number of new establishment deaths, measured at the county and 2-digit NAICS level.

C. Public Disclosure Download Data

To directly examine the consumption of public firm disclosures, we retrieve the server logs associated with the SEC's Edgar website. We define $Log(1 + Downloads)$ as the natural logarithm of one plus the total number of downloads in a given county-quarter. The SEC's server log provides the Internet Protocol (I.P.) address (anonymized), a timestamp, and the physical location of the I.P. address. Our dataset covers the period from 2005 to 2017.

To examine the channel and outcome of consuming public firm information at the entrepreneurial firm level, we obtain a large sample of start-ups from CrunchBase, a crowd-sourced database that tracks start-ups. CrunchBase describes itself as "the leading platform to discover innovative companies and the people behind them." The primary source of data in CrunchBase is TechCrunch, an online publisher of technology industry news. Both TechCrunch and CrunchBase were founded in 2005 and include backfill data from the mid-1990s. Our sample covers the period from 2005 to 2019. We require start-up companies to be in the U.S. and have non-missing values in their geographic location, industry classification, age, and the number of employees. We have 227,310 unique start-up companies. We manually match CrunchBase start-ups with Edgar Server Logs using IP addresses of start-ups to identify their Edgar downloading behavior. We provide summary statistics for this subsample in Online Appendix Table OA5.

D. SBA Loan and Venture Funding Data

To examine whether public firm disclosures help reduce informational frictions between capital providers and entrepreneurs, and thereby facilitate better access to financing for entrepreneurial activities, we use loan data from the Small Business Administration (SBA) and venture capital data from CrunchBase. Specifically, using the SBA loan database, which spans the years 1991 through 2016, we define two small business loan variables $SBA\ Loan\ Count$ defined as the log of one plus the number of loans issued in a county-year, and $SBA\ Loan\ Value$ defined as the log of one plus the total sum of loan values in a county-year. Moreover, using CrunchBase, which spans the years 1995 through 2016, we define two venture funding variables $VC\ Funding\ Count$ defined as the log of one plus the number of VC investments in a county-year, and $VC\ Funding\ Value$ is defined as the log of one plus the total sum of VC investments in a county-year. VC investments include seed-round and series A through J investments. We provide summary statistics in Online Appendix Table OA5.

E. Entrepreneurial Outcomes

To assess whether corporate disclosures facilitate entrepreneurial success, we collect business outcomes of start-ups, including going public (IPO) and being acquired by other companies, from CrunchBase. We use the likelihood of entrepreneurial firms eventually going public or being acquired by other companies because these events provide entrepreneurs with liquidity and financial returns (e.g., Pagano, Panetta, and Zingales, 1998; Aggarwal and Hsu, 2014). Especially, IPOs allow these businesses to access not only diverse equity investors but also diverse debt investors, helping further expansion (Pagano, Panetta, and Zingales, 1998). We provide summary statistics in Online Appendix Table OA5.

F. Summary Statistics

Table 1 provides descriptive statistics for our key variables at the county-quarter level. The average county-quarter in our sample has 371 new business registrations with 2% of the observations occurring after an IPO in the county. The average annual income per capita in the sample is $26,670. Columns (2) and (3) show that counties with at least one IPO are observably different from counties with no IPOs. These differences motivate us to include county fixed effects as outlined in the next section. We also include income per capita, population, and the proportion of public firms as controls to account for these heterogeneities.

III. MAIN EFFECT ANALYSIS

In this section we describe our empirical design as well as the results of our estimation of the relation between IPOs and local new business formation, entrepreneurial interest, and new firm financing. We then conduct tests to rule out the alternative story that economic growth is driving our results rather than information from public disclosure.

A. *IPOs and New Business Formation*

We begin by exploring the base relationship between IPO activity in a county (e.g., a county-headquartered firm going public) and new business formation as measured by the SCP database of new business registrations. We estimate a generalized difference-in-differences (D.D.) model. Because the SCP data does not provide information about the business' industries, our model's variation is across counties. Specifically, we estimate the following generalized difference-in-differences model with staggered treatment:

$$Log(1 + New\ Business\ Reg)_{c,q} = \delta Post\ IPO_{c,q} + \propto_c + \gamma_q + \beta' X_{c,q} + \theta_c q + \varepsilon_{c,q} \quad (1)$$

where we denote county by c and quarter by q. $New\ Business\ Reg_{c,q}$ is the number of new business registrations as reported in the SCP database. $Post\ IPO_{c,q}$ is an indicator variable that equals one for the county-quarters after an IPO and zero otherwise. We include county fixed effects $\propto_c$, quarter-year fixed effects γ_q, and county-specific linear time trends $\theta_c q$. We also include several control variables to capture time-varying economic conditions in the county such as the log of county population and county income per capita. We cluster the standard errors at the county level. This design compares changes in new business registrations in county quarters where an IPO has been initiated to business registrations in county quarters without an IPO.

Table 2 reports the results of estimating various permutations of equation (1). In columns (1) and (2) our main dependent variable is $Log\left(1 + New\ Business\ Reg_{c,q}\right)$ while in column (3) we use $Log\left(New\ Business\ Reg_{c,q}\right)$ as our primary dependent variable and restrict the sample to non-zero observations. We find that areas that experience an IPO see an increase of 7-10% in new business registrations in the quarters after the IPO (even after controlling for time-varying country economic conditions with county-year fixed effects). This increase translates to around 27 to 38 new business registrations on average in the IPO county in the post IPO quarters relative to non-IPO quarters.

Barrios (2021) states that one of the fundamental assumption of the staggered entry DD model is the parallel trend assumption, which states that in absence of the treatment (IPO in the county), the dependent variable of both the treatment and the control groups should exhibit the same trend. We thus assess graphically whether the parallel trends assumption holds in Figure 3. Specifically, Figure 3 graphically presents the difference-in-differences estimates (with each dot representing annual-coefficients) in event time. In both panels, the counterfactual treatment effects in the pre-IPO periods are statistically indistinguishable from zero, providing further support for our inferences (parallel trends in the pre-period). Post-IPO, in contrast, we see a clear increasing treatment effect.

Of course, it is possible that spillover effects between geographically proximate counties may contaminate a subset of our control group. Since our treatment is at the geographic level, the question is what constitutes an independent geographic region. In our setting, the concern is that a neighboring county may not be independent of activity in its neighboring counties with respect to information transmission. For example, to the extent that the informational benefits of a given county's IPOs (the treatment group) positively affect the entrepreneurial activity of a neighboring county, which in our specification is included in the control group, our estimates may be biased downward. We explore this issue in Table OA1 in the Online Appendix. We find that our results that are stronger when we exclude the treated county's immediately neighboring counties, suggesting that our findings in Table 2 are likely conservative. Neighboring counties are likely experiencing some amount of the IPO's spillover effects. Because they are included in our control group, their inclusion will attenuate our estimates. Additionally, we find that inter-county spillover effects dissipate rapidly with distance. We find muted effects when examining counties that are "two-degrees removed" from the treatment county, suggesting that our control group in general (except for the closest neighbors) likely satisfies the SUTVA assumption.

While the difference-in-differences setup we employ utilizes staggered arrival of IPOs in the county to identify the effects on new business formation, a reasonable concern is that the emergence of IPOs in a county may not be exogenous but may relate in some way to county-specific attributes that vary over time and which also influence the formation of new businesses. While the IPO event typically signals that a firm has reached a stage in which its business is no longer likely to be limited to its local headquarters market, we nevertheless next provide analysis that addresses the endogenous nature of IPOs (Aghamolla and Guttman, 2020).

We follow Bernstein (2015), who utilizes the fact that some IPOs are filed but not undertaken, but instead are withdrawn due to sudden changes in market conditions. Following the Bernstein (2015) approach, we instrument for IPO completions at the firm-level using the NASDAQ return in the two months following the IPO filing date. This provides us with firm-level likelihoods of an IPO based on the NASDAQ returns immediately following the filing. Specifically, we estimate the following first-stage regression:

$$IPO_{i,c,q} = \alpha + \beta NASDAQ\ Returns_{i,c,q} + \gamma X + \ + \propto_c + \ \gamma_q + \ \varepsilon_{c,q} \qquad (2)$$

for filer i in country c and quarter q. IPO is the dummy variable of interest, indicating whether a filer goes public or remains private. $NASDAQ\ Returns$ are two-month returns after the IPO filing date. We include county fixed effects $\propto_c$ and quarter-year fixed effects γ_q. We include a vector of control variables, X, which include the log of county population and county income per capita. We cluster the standard errors at the county level.

Panel A of Table 3 presents the estimates from the first stage of the IV. As in Bernstein (2015), NASDAQ returns are significant and strong predictors of an IPO completion. Because our unit of analysis is the county-quarter, we next aggregate the firm level first-stage estimates to the county-quarter level by averaging or summing across IPO filers in the county-quarter when the county had its first IPO(s). Prior to the first IPO the measure is zero. Thus, the second-stage equation estimates the impact of IPO on new business registration:

$$Log(1 + New\ Business\ Reg)_{c,q} = \ \delta \widehat{IPO}_{c,q} + \ \propto_c + \ \gamma_q + \ \beta^{'}\ X_{c,q} + \ \varepsilon_{c,q} \qquad (3)$$

where $\widehat{IPO}_{c,q}$ are the aggregated predicted values from the first-stage regression. We aggregate the first-stage estimates values at the county-quarter when the county first had its first IPO(s) by either summing or averaging each of the first-stage fitted values.

The estimates are reported in Panel B of Table 3. Consistent with the difference-in-differences estimation in the preceding table, we observe a positive and statistically significant coefficient on the instrumented IPO variable, regardless of whether we use the average across firms in the county or the sum across firms in the county, of slightly larger magnitude than in the non-instrumented models. The estimates suggest a strong causal relationship between a new IPO in the county and subsequent new business formation.

B. *IPOs and Entrepreneurial Interest*

Until now, we have documented a positive link between our public firm disclosure proxies and new business formation. We now turn to a measure that captures general interest in entrepreneurial activity more broadly: internet searches for terms and phrases directly related to launching a business—what is referred to in the literature as entrepreneurial interest (Barrios et al., 2020).[2] This measure provides us with a timelier response to spillovers from the IPO by examining whether IPO activity in the county leads individuals to begin contemplating entrepreneurship.

[2] We track trends for searches for these terms using the Google Health Trends API for all Nielsen Designated Market Areas (DMAs) at monthly frequency from January 2004 to December 2016. We aggregate the data to the quarter level and match the DMAs to Census incorporated places using a crosswalk provided by Nielsen. Specifically, we use the terms: "start a business," "start your own business," "start a company," "how to incorporate," "entrepreneurship," "become an entrepreneur," and "small business loan." See Barrios et al. (2020) for more details.

Table 4 employs a linear probability model to estimate a variation on equation (1) above at the DMA level. The outcome is an indicator variable that is defined as one in the case that the DMA is in the top quartile of entrepreneurial search in that quarter. Each specification includes controls for population, per capita income, and the number of public firms headquartered in the area. Our variable of interest is the $Post\ IPO$ variable, which captures exposure to public firm information being produced by the IPO. The specification includes year and state fixed effects. Table 4 indicates that after an IPO, the affected county is more likely to be in the highest quartile of entrepreneurial search activity. In terms of economic magnitude, the 1.5% increase in the probability translates to a 6% increase over the base probability of 25%.

C. IPOs and Establishment Births

Next, we turn to establishing birth as an alternative proxy for entrepreneurial activity using the SUSB data described in Section III. A key advantage of this data is that it allows us to observe industry information. To test whether establishment births are influenced by IPO activity, we run the following regression:

$$Log(1 + Establishment\ Birth)_{c,i,t} = \delta Post\ IPO_{c,i,t} + \propto_c + \mu_i + \gamma_t + \beta' X_{c,t} + \varepsilon_{c,i,t} \tag{4}$$

with observations measured at the county c, industry i, and year t level. $Establishment\ Birth_{c,i,t}$ is the number of new establishment births in the county-industry-year, as taken from the Census database. We include county $\propto_c$, industry μ_i, and year γ_t fixed effects. Finally, $X_{t,c}$ is a vector of time-varying county-specific control variables, including the log of population and income per capita. We cluster standard errors at the county level. Our coefficient of interest, δ, captures the percentage increase in entrepreneurial activity associated with a one quintile increase in public firm presence in an industry.

Table 5 provides the results of estimating equation (1). Column (1) demonstrates a positive link between $Log(1 + Establishment\ Birth)_{c,i,t}$ and $Post\ IPO_{c,i,t}$. We find an 40% increase in the number of establishment births for an industry-year-county in which an IPO happens. Columns (2) similarly shows that this relation is robust to using $Log(Establishment\ Birth)_{c,i,t}$ as the dependent variable, where we restrict the sample solely to observations with positive establishment births.

To examine the cumulative effect of IPOs, we consider public firm presence. Public Firm Presence is defined as the proportion of public firms in each NAICS 3-digit industry-year, following Badertscher et al. (2013) and Shroff et al. (2017). The measure can be viewed as a cumulative measure of IPOs. Data on the total number of firms in each industry is obtained from the Census Bureau, and we proxy for the number of public firms in each industry using data from Compustat. To minimize the influence of outliers, we sort Public Firm Presence into quintiles each year to create the variable Pub Firm Presence Quintile. We present this analysis in Table OA2 in the Online Appendix. Consistent with our IPO findings, we find qualitatively similar results with this measure of public firm presence, furthering the notion of an information channel mechanism.

D. *Entrepreneurial Financing*

Next, we provide further evidence of the spillovers to entrepreneurial activity by exploring the effect of IPOs on new business financing. We use loan data from the Small Business Administration (SBA) and venture capital data from Crunchbase. The ability to access financing is an essential driver of entrepreneurial success but it is often met with frictions that prevent entrepreneurs from accessing capital (e.g., Leland and Pyle, 1977; De Meza and Webb, 1987; Hochberg, Serrano, and Ziedonis, 2018). Specifically, the lack of information over borrowers and investees is one of the critical frictions that can prevent entrepreneurs from obtaining capital (e.g., Baron and Holmstrom, 1980; Rock, 1986; Benveniste and Spindt, 1989). In other words, IPOs can reduce information asymmetry between entrepreneurs and investors and across investors about these entrepreneurs by providing information about these new businesses' prospects. Thus, the advent of the IPO and the informational spillovers associated with the IPO could lead to a relaxation in financing frictions and an increase in overall funding activities.

In Table 6, we provide evidence that entrepreneurial ventures raise more financing following an IPO in the county. In column (1), we explore the number of loans to newly registered businesses. The estimates suggest that an IPO in the local area leads to a 22% increase in the number of loans to newly registered businesses, off an unconditional mean base of 1.49 loans. In column (2), we look at the dollar volume of loans. The estimates suggest that an IPO in the local county leads to a subsequent 52% increase in the total dollar volume of loans to newly formed businesses, suggesting an increase in the size of loans as well as in the number of loans following an IPO. In columns (3) and (4) of Table 6, we find qualitatively similar evidence consistent with public disclosures having a positive impact on venture capital financing, for both the number of deals in the county-year and dollar volume of financing raised.

Overall, the results for the financing channels are thus consistent with the findings in our main analysis that support an increase in new business registrations overall following a local

IPO and hint at the potential information spillover of IPOs to capital providers as to the quality of these entrepreneurial businesses.

E. *Are We Merely Picking Up Economic Growth?*

An obvious concern is that our results above may be driven by concurrent economic growth in the county, that in turn drives new business formation. While the parallel trends exhibited by our models suggest this is not a primary concern, we can also test directly for evidence of economic growth following a local IPO. In Table 7, we follow Barrios et al (2021), and estimate models using average weekly wage as the outcome measure, using a similar specification to the previous analyses. We fail to document significant increases in average weekly wages or employment post IPO activity in the local area, suggesting that our observed increases in entrepreneurial activity surrounding an IPO are unlikely to be solely driven by the growth of the local economy.

IV. INFORMATION MECHANISM ANALYSIS

If economic growth does not drive the increase in new business formation, what does? We hypothesize that the information in new IPO firm disclosures reduces uncertainty regarding future returns to entrepreneurial activities, thus increasing entrepreneurial entry following IPO events. Next, we test for evidence consistent with this information story. We show that the increase in new business formation is largest in areas with greater economic uncertainty, where information is more valuable to potential entrepreneurs. We then explore how new business registrations relate to download of public disclosures.

A. *Economic Uncertainty*

To explore the importance of IPOs' information production, we examine a case where public firm information should be more valuable to entrepreneurs: locations where economic uncertainty (and in turn, entrepreneurial income uncertainty), is higher.[3] We expect the role of information to be most pronounced when economic uncertainty is high in a given county. We operationalize the economic uncertainty proxy by constructing a measure of the volatility in wage growth in each county (Barrios et al., 2020). [4] For this purpose, we utilize data from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW). Wage growth volatility is computed as the sum of the variances and covariances of the wage growth rate in the various industry sectors, weighted by the employment share of each individual sector. We compute this measure at the county level.

First, we derive a variance-covariance matrix from a trend-adjusted time series of county-industry employment data. Mathematically, the measure of wage growth volatility for the portfolio of industries in a given county is then expressed as:

$$\sigma_c^2 = \sum_i w_i^2 \sigma_i^2 + \sum_{i \neq j} \sum_{i \neq j} w_i w_j \sigma_{ij} \tag{4}$$

where w_j denotes the proportion of total employment in industry j, σ_j^2 denotes the variance of wage growth rate in industry j, and c denotes county. Figure 4 shows the relationship between

[3] Conceptually, we can think of economic profits as reflecting demand shocks to industries, which in turn also lead to variation in wage growth. Under a rent-sharing perspective, whenever there is a demand shock that leads to change in profits, this change is shared between the firm and labor (Kline et al., 2019).

[4] Ideally, we would use variation in economic profits in an area to proxy for economic uncertainty, but data on business profits is unavailable.

our wage growth volatility measure and new business registration. We absorb time and location fixed effects. As the scatter plot demonstrates, the relationship between wage growth volatility and entrepreneurial entry is negative, consistent with economic uncertainty discouraging entrepreneurial activity.

In Table 8, we utilize our proxy for economic uncertainty—the volatility of wage growth in the county—and estimate DD models including the interaction of a standardized (mean zero, standard deviation one) version of our ex-ante uncertainty measure with the $POST\ IPO$ variable in the models. We measure wage growth volatility for each county using all quarters up to the quarter before entry (or all quarters, if no entry occurs during the sample period). Because this measure in not at the annual level, but instead measured once per county, the lower order term (pre-entry wage growth volatility itself) is absorbed by the county fixed effects. Consistent with an information channel, the models in Table 8 indicates that the positive effects of the IPOs on new business formation are concentrated in counties with higher ex-ante economic uncertainty. Specifically, the estimates translate into an additional 40 percentage point increase in new business registrations for the top quartile of ex-ante economic uncertainty, on top of the main effect IPOs. The effect in counties in the top quartile of ex-ante uncertainty (1.93%) is about five times larger than the average of the bottom three quartiles of ex-ante economic uncertainty (0.48%). This bolsters the view that new public firm disclosures provide valuable information for potential entrepreneurs.

In the Online Appendix, we conduct two additional sets of analysis to validate the information mechanism further. We explore two situations where we may expect public firm information to be more valuable to entrepreneurs. First, we demonstrate that the effects we document are stronger for IPOs of new, independent, private firms than spinoff IPOs of public firm subsidiaries. When a subsidiary is spun out and goes public, less incremental information is likely generated, as the parent corporation was already producing public disclosures prior to the IPO. Accordingly, in Table OA3, we find that entrepreneurial activity increases primarily around IPOs of private firms. Second, we examine situations where a county has already experienced a recent IPO, and subsequently experiences another. We expect that when the subsequent IPO is of a firm from a different industry than the first IPO, more information is transmitted, and we should therefore see a more pronounced effect on new business registrations. In Table OA4, we show that our results are more pronounced when a subsequent IPO (of a county that had experienced an IPO previously) is from a different industry than a previous IPO in the same county. This is consistent with the idea that IPOs are more likely to provide new/incremental information when the IPO is from a new industry.

B. Information Acquisition

An important ramification of an information mechanism contributing to the positive link between our disclosure proxy (IPO) and new business formation is that we should expect more intense information acquisition patterns due to the IPO event. To do this, we first show that downloads of public filings from Edgar are higher in counties that experience an IPO. Then we show that new business registrations are higher in counties that actively download these filings. Furthermore, we show that the positive relationship between an IPO and new business formation is magnified in counties with high levels of S-1 downloads.

The results of our analysis are reported in Table 9. In Table 9, Panel A, the dependent variable is the natural logarithm of the number of post-IPO Edgar downloads in the county quarter, and the independent variable of interest is an indicator for post-IPO in the county. The sample for this analysis is based on 8-quarters before vs. after the first IPO since 2005. The sample period spans the years 2005 through 2016. We utilize four different measures of Edgar downloads. In column (1), $Log(1 + sum\ all)$ is defined as the log of one plus the total number of Edgar downloads across all file types. In columns (2) through (4), $Log(1 + sum\ S1)$, and $Log(1 + sum\ 10K)$ are defined as log of one plus the total number of downloads for both S1 and 10K filings. Regardless of the specification of the dependent variable, we observe a strong positive and a statistically significant increase in Edgar downloads following an IPO in the county.

In Panel B of Table 9, we regress $New\ Business\ Registrations$ on indicators for being above the sample-period median on each of our four measures of Edgar downloads in the county quarter, as well as controls (and year-quarter-fixed effects in column (2)). Standard errors are robust and clustered at the county-level. Consistent with information from the IPO driving new business entry, we observe a positive and significant relationship between high downloads of S-1 filings and new business registrations. In contrast, the other types of filings do not load significantly. Once again, the estimates are consistent with a role for information in driving new business formation in the county following a public offering of a local firm.

Next, we go on to examine further the extent to which the downloading of public filings serves to magnify the relation between an IPO and new business formation. Specifically, in Panel C of Table 9, we regress our measure of $New\ Business\ Registrations$ on interactions of the post-IPO indicator with indicators for being above the sample-period median on each of our two measures of Edgar downloads in the county quarter. Explicitly, we estimate the following equation:

$$Log(1 + New\ Business\ Reg)_{c,q}$$
$$= \delta Post\ IPO_{c,q} + \gamma_{10K}\ Post\ IPO_{c,q} * High(sum_{10K}) + \gamma_{S1} Post\ IPO_{c,q} * High(sum_{S1}) + \propto_c + \gamma_q + \varepsilon_{c,q} \tag{6}$$

Panel C of the table presents the estimates. We observe that the relationship between the IPO and new business formation is, in fact, magnified by the reliance on public filings of S-1s in particular. This further bolsters the information channel as the mechanism for the positive relationship observed between an IPO and new business formation above. These findings are consistent with the view that public firm disclosures inform entrepreneurs, raising the bar for an alternative mechanism, such as industry growth prospects, to explain our results.

Finally, we narrow down our analysis to Edgar download activities of sophisticated entrepreneurs, assuming that sophisticated entrepreneurs are more likely to use public disclosure information. Presumably, innovation-driven new businesses, which are likely to seek venture capital investment, are founded by more sophisticated entrepreneurs, compared to new small businesses or traditional businesses such as a corner grocery store or laundry. CrunchBase tracks innovation-driven startups. We identify the IP addresses of Crunchbase firms using name matching as described in Section II. We then match the IP addresses to Edgar downloads to determine the download activity of each startup. This process allows us to focus on sophisticated entrepreneurs' business activities and information acquisition around IPOs. We develop two measures: the log number of CrunchBase firms that download at least one Edgar file in a county-year ($Log(1 + Edgar\ Downloading\ Entrepreneurial\ Firms)$) and the log average number of Edgar file downloaded in a county-year ($Log(1 + Entrepreneurial\ Downloads)$).

The estimates are presented in Table 10. We find that both the number of CrunchBase firms that download at least one Edgar filing in a county-year and the average number of Edgar files downloaded in a county-year are positively associated with the $Post\ IPO$ variable. These positive relations indicate that CrunchBase entrepreneurs begin to more actively use public disclosure as newly public IPO firms disclose information to the market. In economic terms, we document a 16% increase in Edgar downloading CrunchBase firms, and a 66% increase in total Edgar downloading activity among CrunchBase firms. To contextualize these findings, the documented effect implies 6.1 additional CrunchBase firms downloading from Edgar (145.7 total additional entrepreneurial Edgar downloads) per year relative to the baseline average.[5]

C. Impacts on Entrepreneurial Outcomes

Our analysis, up to now, provides evidence that the information generated by public firm disclosures plays a role in facilitating the formation of new local businesses. We next present a first attempt to analyze the economic consequences of such information for these new businesses. Specifically, we examine whether the consumption of public firm disclosures is positively associated with the entrepreneurial firm's ultimate outcome. We focus on the firm ultimately being acquired or going public.

In Table 11, Panel A, we present the estimates for tests for whether public firm information consumption by start-ups, as captured by their Edgar downloads, predicts future business success. The independent variable, Edgar Downloads, is an indicator variable that equals 1 if the start-up downloads at least one Edgar Filing before the end of 2010. The outcome variables

[5] Specifically, we multiply the 16% Crunch Base firm effect (66% total Edgar downloading effect) to their respective raw averages of 0.12 (0.45) and multiply that number to the average number of yearly IPOs during our sample, which is 272.

are indicators of the start-up going IPO (column (1)), being acquired (column (2)), or either going IPO or being acquired (column (3)) after 2010. The results suggest that start-ups that actively consume public firm information are 27% and 13% more likely to have an IPO or be acquired, respectively, than those that do not do so.

Our analysis, while providing some initial evidence consistent with the information being efficient, is not meant to establish a causal relation between information spillovers and firm outcomes. Moreover, we caution that inferences from information and entrepreneurial outcome tests do not provide sufficient evidence about welfare consequence. We view our tests as a first attempt to study the economic consequences of information on entrepreneurial success. As such, our results suggest that additional research is warranted to understand the impact of information on entrepreneurial outcomes.

V. CONCLUSION

In this paper, we explore whether and how IPO activity in the local region facilitates new business formation. Understanding the determinants of the geographic distribution of entrepreneurial activity has become an issue of primary importance for policymakers seeking to take advantage of the economic growth effects of new business activity. We show that in the wake of an IPO, new business formation in the county is accelerated.

We then explore a potential mechanism for this effect: information spillovers. Specifically, we consider whether newly IPOed firm public accounting disclosures provide information that can potentially inform entrepreneurs in their decisions to start a new business and financiers in their decisions to support those new businesses. Our findings suggest that the provision of information from public firm disclosures reduces uncertainty related to entrepreneurial income volatility, thus increasing entrepreneurial activity with small business loans and venture capital and galvanizing would-be entrepreneurs to engage in new business formation.

Our work speaks to two fundamental questions, one in accounting and one in entrepreneurship. One of the fundamental questions in accounting is whether and to what extent financial reporting facilitates capital allocation to investment opportunities (Roychowdhury et al., 2019). To date, the primary focus of the literature on the public disclosure learning channel has been on the intensive margin—the firm's investment efficiency. In this paper, we build upon this work and explore how public firm disclosure may affect learning on the extensive margin, in the form of new business formation.

Additionally, our results contribute to the fundamental question of what drives new business formation. Economists since Adam Smith have emphasized the importance of entrepreneurs and new business formation to the economy. Our results support the existence of an information channel for local entrepreneurial activity, and suggest the need for future research exploring the role of information and access to it for new business formation. We look forward to more work that pushes this new frontier between information and entrepreneurial activities in other settings.

APPENDIX A. VARIABLES DEFINITION

Name	Definition	Source
Log(1+New Business Reg)	Log of one plus the number of new business registrations	Startup Cartography
Post IPO	Indicator variable that is set to one in county quarters after an IPO event	Thomson SDC
Log Population	Log of total population in the area	Census
Log Num Pub Firm	Log of the number of public listed firms in the area, where area is either state or county	Compustat
Log Income Per Capita	Log of income per capita in the area	Census
High Entr Search Share	Indicator variable equal to one if entrepreneurial search is in the top quartile. Entrepreneurial search includes: "start a business," "start your own business," "start a company," "how to incorporate," "entrepreneurship," "become an entrepreneur," and "small business loan."	Google Search
Avg Wage Growth	Average wage growth in a county-year	Census
Avg Emp Growth	Average employment growth in a county-year	Census
High Ex-ante Uncertainty	Volatility in wage growth in each county, computed as the sum of the variances and covariances of the wage growth rate in the various industry sectors, weighted by the employment share of each sector	Census
Log(1+Establishment Birth)	Log of one plus the number *Establishment Births*. Where *Establishment Births* are of establishments that have zero employment in the first quarter of the initial year and positive employment in the first quarter of the subsequent year.	Census
Log(1+Establishment Death)	Log of one plus the number *Establishment Deaths*.	Census
Income Growth	Growth of income in the area	Census
Log(1+sum all)	Log of one plus the total number of Edgar downloads across all file types.	SEC
Log(1+Edgar Downloading Entrepreneurial Firms) and Log(1+Entrepreneurial Downloads)	Log(1+Edgar Downloading Entrepreneurial Firms) is the log number of CrunchBase firms that download at least one Edgar file in a county-year. Log(1+Entrepreneurial Downloads) is the log total number of Edgar files downloaded in a county-year.	CrunchBase
SBA Loan	SBA Loan Count is defined as the log of 1 plus the number of loans issued in a year, and SBA Loan Value is defined as the log of 1 plus the total sum of loan values in the year.	SBA
VC Funding	VC Funding Count is the log of 1 plus the number of VC investments in a year, and VC Funding Value is the log of 1 plus the total sum of VC investments in a year. VC investments include seed-round and series A through J investments.	CrunchBase

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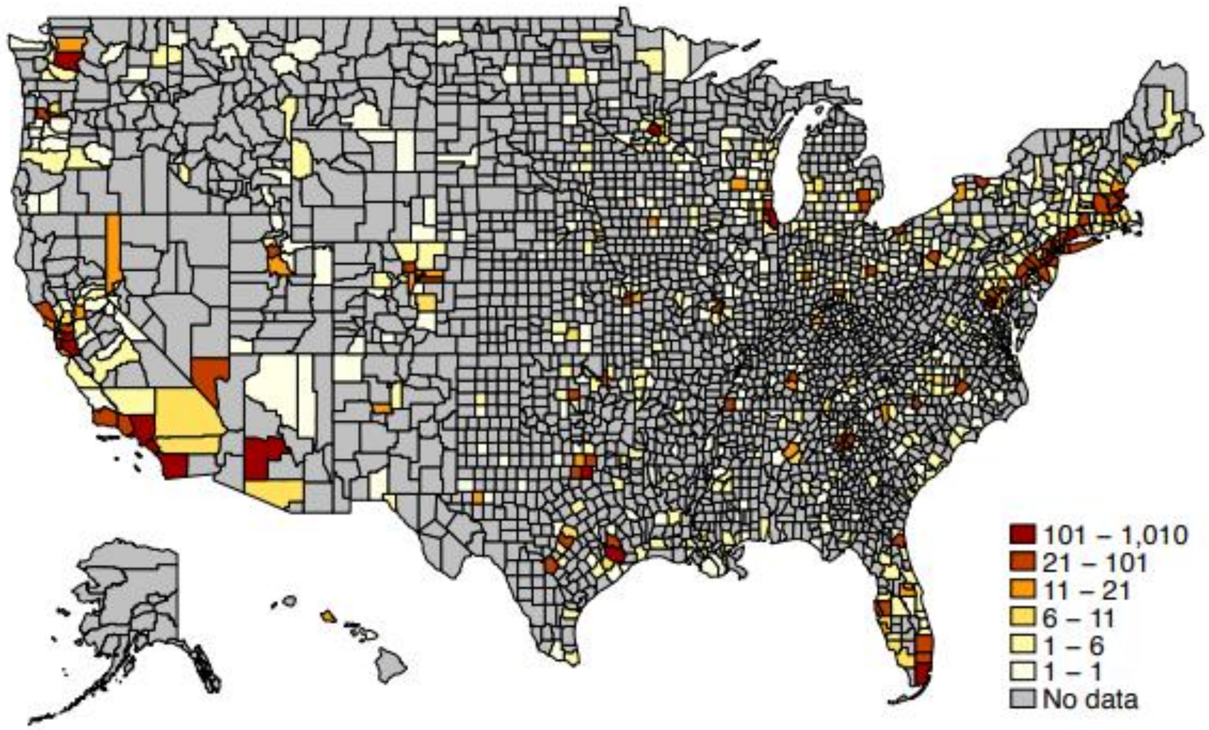
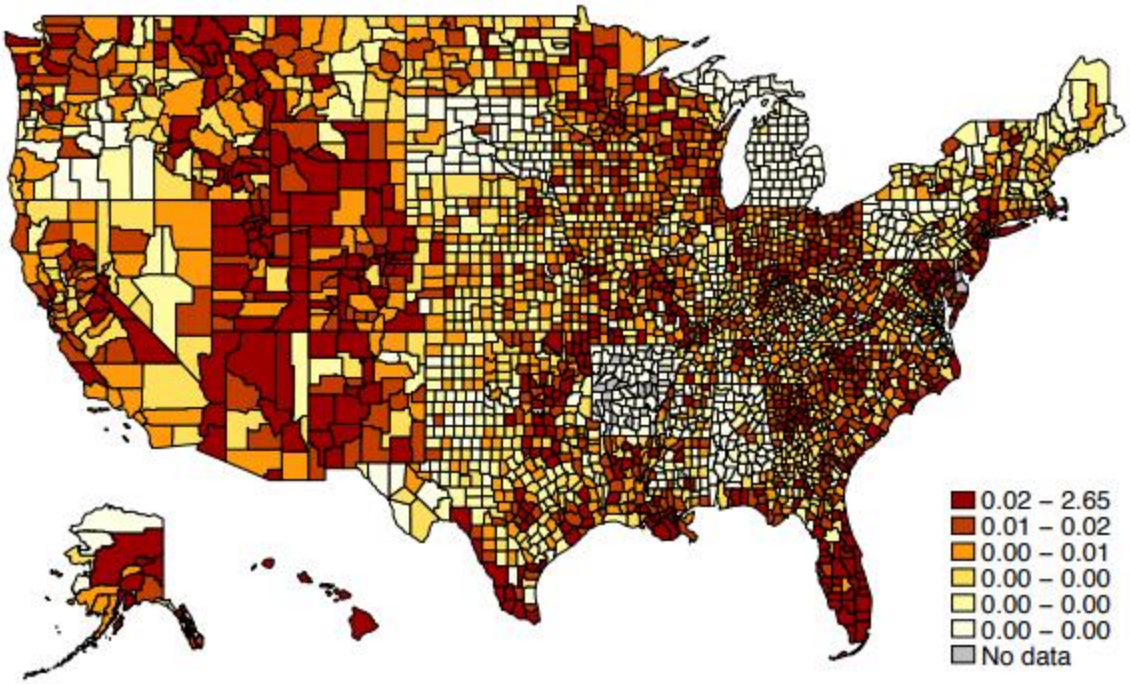
TABLES AND FIGURES

Figure 1. Distribution of IPOs by County



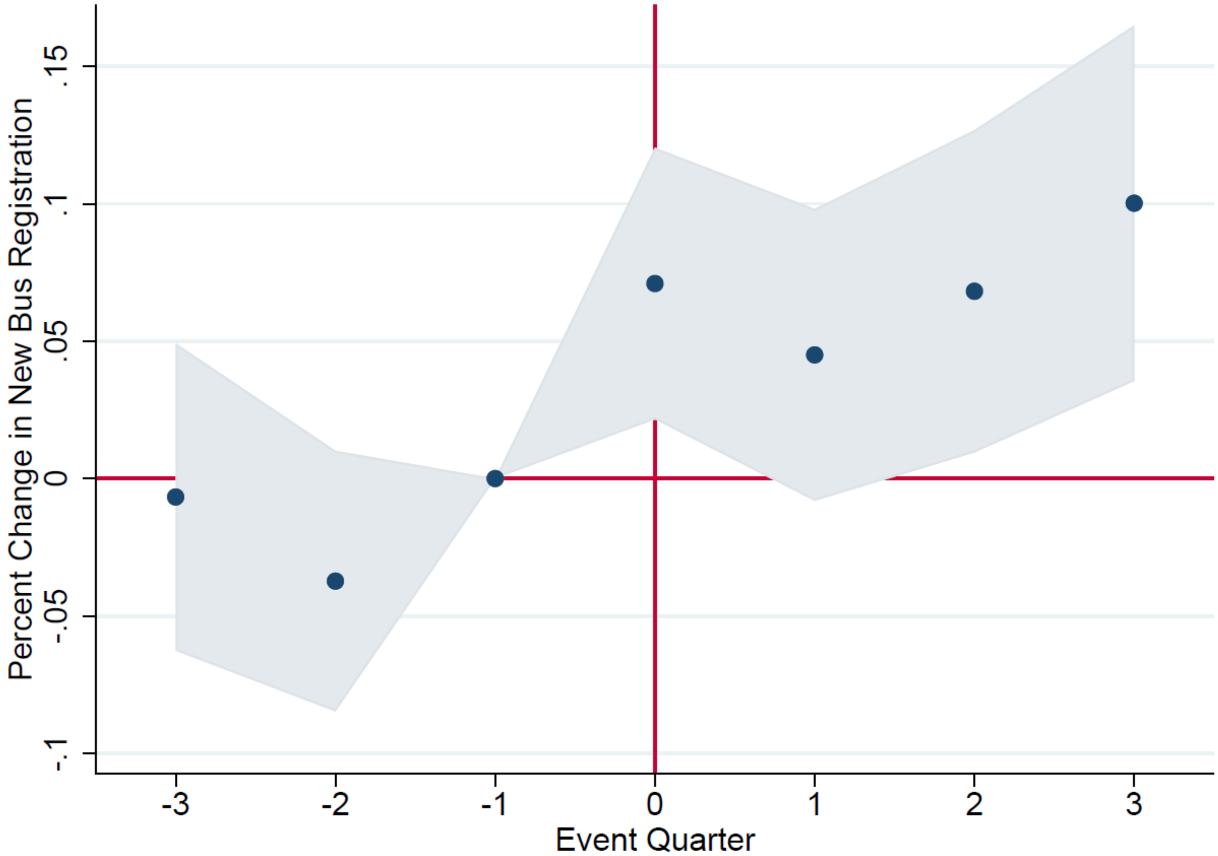
Notes: This figure plots the geographic distribution of 10,734 IPOs across U.S. Counties. The sample period is from 1985 Q1 to 2019 Q4.

Figure 2. New Business Registration by County



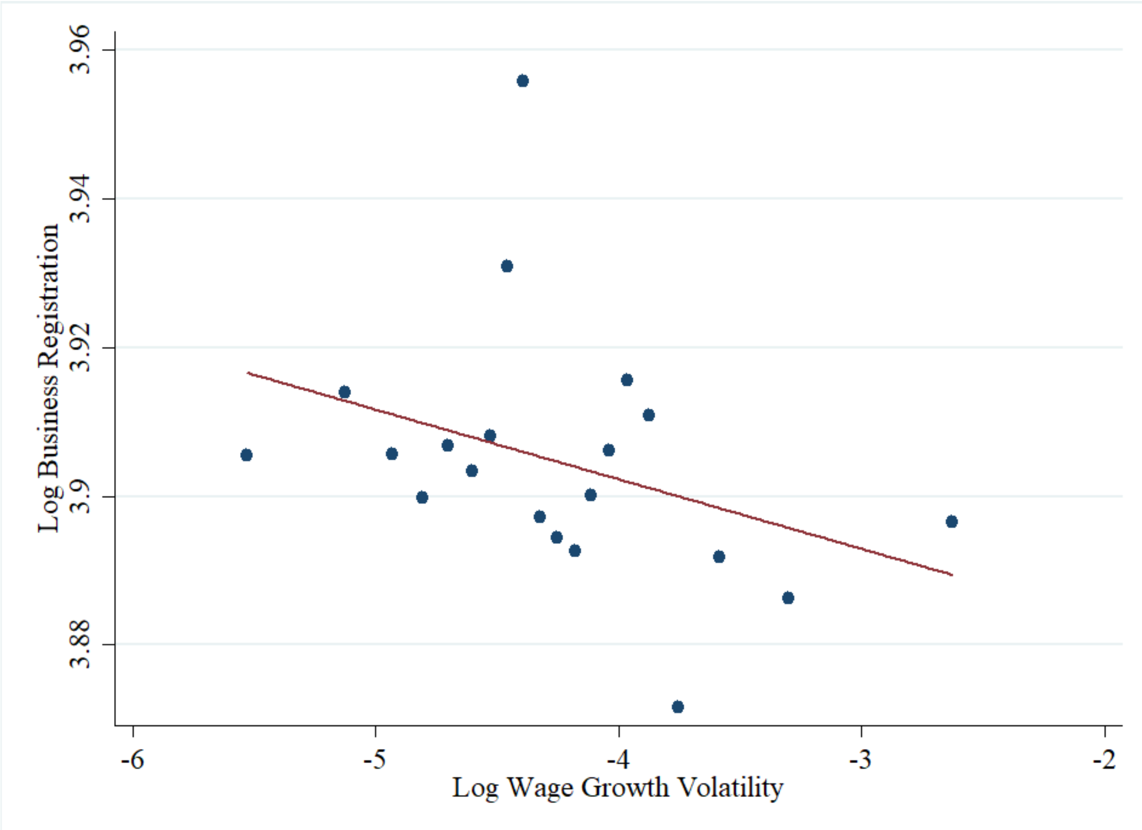
Notes: This figure plots the geographical distribution of annual average new business registration per capita across U.S. Counties. The sample period is from 1988 to 2016.

Figure 3. Parallel Trends of New Business Registration around IPO Event



Notes: This figure plots Model (3) regression coefficient estimates in 7 quarters around the event window. Each dot is a point estimate of δ in equation (3) by shifting $Post$ from Post_{q-4} to Post_{q+3}. The shaded region represents two-tailed 95% confidence intervals based on standard errors clustered at the county level.

Figure 4. Economic Uncertainty and New Business Registration



Notes: The figure plots the relationship between wage growth volatility and new business registration. Wage growth volatility at the county level is computed as the sum of the variances and covariance of the wage growth rate in the various industry sectors, weighted by the employment share of each individual sector in the county. We absorb time and location.

Table 1. Descriptive Statistics

	(1)				(2)				(3)			
	All				County: At Least 1 IPO				County: No IPO			
	count	mean	sd	p50	count	mean	sd	p50	count	mean	sd	p50
New Business Registration	359,892	371	2,451	18.00	75,800	1,313	4,626	174	284,092	119	1,265	11
Num Public Firm	359,892	0.10	1.06	0.00	75,800	0.46	2.28	0.00	284,092	0.00	0.07	0.00
IPO	359,892	0.02	0.26	0.00	75,800	0.10	0.55	0.00	284,092	0.00	0.00	0.00
Income Per Capita	359,892	26,670	11,181	24,808	75,800	31,518	134,745	29,341	284,092	25,376	10,098	23,758
Population	359,892	92,063	314,529	24,856	75,800	316,598	632,045	138,325	284,092	32,145	41,030	19,064
Observations	359,892				75,800				284,092			

Notes: This table presents summary statistics for the sample of new business registration data from the Startup Cartography Project. The sample is at the county-quarter level. Columns (2) and (3) show these statistics across counties with at least one IPO vs. counties with no IPO activity.

Table 2. IPOs and New Business Registration

	(1) Log(1+New Bus Reg)	(2) Log(1+New Bus Reg)	(3) Log(New Bus Reg)
Post IPO	0.1020***	0.0739***	0.0878***
	(0.0385)	(0.0239)	(0.0225)
Log Population	0.9508***		
	(0.0510)		
Log Income Per Capita	0.5863***		
	(0.0582)		
Log Num Pub Firm	0.0903*		
	(0.0464)		
Observations	359,892	359,892	304,897
Year-Quarter F.E.	Yes	No	No
County-Year F.E.	No	Yes	Yes
County F.E.	Yes	No	No
Quarter F.E.	No	Yes	Yes
Cluster	County	County	County
Adjusted R-squared	0.891	0.945	0.949

Notes: This table reports estimation of Model (1) that regresses the number of new business registrations on IPOs. Post IPO is an indicator variable that equals one if a county has an IPO in the past, and zero otherwise. Panel A reports the results of all new business registrations from and after an IPO event in a county. Panel B reports the results of re-estimating the specification of Panel A column (2) by varying the measurement of new business registrations. Specifically, we use the number of new business registrations four quarters ahead in column (1), five quarters ahead in column (2), six quarters ahead in column (3). Standard errors clustered at the county level are reported in parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table 3. Causal Estimates of IPO on New Business Registration

Panel A. First Stage

	(1) IPO
NASDAQ Returns	0.2368***
	(0.0699)
Observations	9,311
Controls	Yes
Year-Quarter F.E.	Yes
County F.E.	Yes
Cluster	County
Adjusted R-squared	0.127

Panel B. Fitted IPOs and New Business Registration – Full Sample

	(1) Log(New Bus Reg+1)	(2) Log(New Bus Reg+1)
Post IPO Hat Sum	0.1372***	
	(0.0479)	
Post IPO Hat Avg		0.1491***
		(0.0510)
Observations	359,892	359,892
Controls	Yes	Yes
County-Year F.E.	Yes	Yes
Quarter F.E.	Yes	Yes
Cluster	County	County
Adjusted R-squared	0.891	0.891

Notes: Panel A presents the first-stage estimation of the instrumental variables analysis. Following Bernstein (2015), the dependent variable is a dummy variable that equals to one if a firm completes an IPO filing, and zero otherwise. *NASDAQ Returns* are two-month returns after the IPO filing date. Panel B presents the second-stage estimation using the fitted IPO values estimated from the first-stage in Panel A. Specifically, *Post IPO Hat Sum* aggregates the firm level first-stage estimates by summing across firms in the county-quarter when the county had its first IPO(s) and equals to zero before that quarter. Similarly *Post IPO Hat Avg* aggregates the firm level first-stage estimates by averaging across firms in the county-quarter when the county had its first IPO(s) and equals to zero before that quarter. Control variables include the following three variables. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the log number of population at the county-year level. Log Num Pub Firm is the log number of public listed firms in the state. Standard errors clustered at the county level are reported in parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table 4. IPOs and Entrepreneurial Interest

	(1) P(High Entr Search Share)
Post IPO	0.0279*
	(0.0146)
Observations	40,212
Controls	Yes
Year F.E.	Yes
State F.E.	Yes
Cluster	State
Adjusted R-squared	0.158

Notes: This table reports estimation of Model (1) as a linear probability model that regresses entrepreneurial search intensity on IPOs. The outcome variable, High Entr Search Share, is an indicator variable that is defined as one in the case that the DMA is in the top quartile of entrepreneurial search intensity in that quarter. We measure entrepreneurial search intensity using internet searches for terms and phrases directly related to launching a business as in (Barrios et al., 2020). Post IPO is an indicator variable that equals one if a county has an IPO in the past and zero otherwise. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the log number of population at the county-year level. Log Num Pub Firm is the log number of public listed firms in the state. Standard errors clustered at the state level are reported in parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table 5. IPOs and Establishment Births

	(1) Log(1+Establishment Birth)	(2) Log(Establishment Birth)
Post IPO	0.3979*** (0.0263)	0.2884*** (0.0245)
Observations	866,359	598,813
Controls	Yes	Yes
Year F.E.	Yes	Yes
County F.E.	Yes	Yes
Industry F.E	Yes	Yes
Cluster	County	County
Adjusted R-squared	0.781	0.792

Notes: This table reports estimation regressing the number of new establishment births on IPOs. This table reports the results of IPOs from the same industry as the new establishments. Establishment Birth is the number of new establishments in an industry and county-year. Post IPO is an indicator variable that equals one if a county has an IPO in the past, and zero otherwise. Control variables include the following three variables. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the log number of population at the county-year level. Log Num Pub Firm is the log number of public listed firms in the state. Standard errors clustered at the county level are reported in the parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table 6. IPOs and Entrepreneurship Financing

	(1) SBA Loan Count	(2) SBA Loan Value	(3) VC Funding Count	(4) VC Funding Value
Post IPO	0.2224***	0.5248***	0.7726***	0.0426***
	(0.0219)	(0.1091)	(0.1089)	(0.0086)
Observations	313,664	313,664	265,408	265,408
Controls	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes
County F.E	Yes	Yes	Yes	Yes
Cluster	County	County	County	County
Adjusted R-squared	0.806	0.559	0.493	0.628

Notes: This table presents the results of regressing entrepreneurship financing data on IPO. Post IPO equals 1 in the year when the county has its first IPO and remains 1 thereafter. Columns (1) and (2) measure small business loan financing from 1991 to 2016 on a county-year basis using data obtained from the Small Business Administration. SBA Loan Count is defined as the log of 1 plus the number of loans issued in a year, and SBA Loan Value is defined as the log of 1 plus the total sum of loan values in the year. Columns (3) and (4) measure venture capital financing from 1995 to 2016 on a county-year basis using data obtained from Crunchbase. VC Funding Count is the log of 1 plus the number of VC investments in a year, and VC Funding Value is the log of 1 plus the total sum of VC investments in a year. VC investments include seed-round and series A through J investments. Control variables include the following three variables. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the log number of population at the county-year level. Log Num Pub Firm is the log number of public listed firms in the state. Standard errors clustered at the county level are reported in the parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table 7. IPOs and Economic Growth Placebo

	(1) Avg Wage Growth	(2) Avg Emp Growth
Post IPO	-0.0007	0.0002
	(0.0008)	(0.0013)
Observations	210,702	210,702
Controls	Yes	Yes
Year-Quarter F.E.	Yes	Yes
County F.E.	Yes	Yes
Cluster	County	County
Adjusted R-squared	0.406	0.0629

Notes: This table reports estimation of regressions of average wage growth and average employment growth on IPOs. The sample period is from 2000 Q1 to 2016 Q4 as average wage growth and average employment growth data is available in this period. Post IPO as an indicator variable that is set to one in county quarters after an IPO event. Control variables include the following three variables. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the log number of population at the county-year level. Log Num Pub Firm is the log number of public listed firms in the state. Standard errors clustered at the county level are reported in the parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table 8. IPOs, New Business Registrations, and Uncertainty

	(1) Log(1+New Bus Reg)	(2) Log(New Bus Reg)
Post IPO X High Ex-ante Uncertainty	0.4008**	0.4200**
	(0.1604)	(0.1692)
Post IPO	-0.0315	-0.0633
	(0.0872)	(0.0895)
Observations	290,072	145,072
Controls	Yes	Yes
Year-Quarter F.E.	Yes	Yes
County F.E.	Yes	Yes
Cluster	County	County
Full Interaction	No	No
Adjusted R-squared	0.857	0.866

Notes: This table reports estimation of how the impact of IPO on new business registrations depends on local economic uncertainty. The sample period is from 2000 Q1 to 2016 Q4 as wage growth data is available in this period. $Post\ IPO$ as an indicator variable that is set to one in county quarters after an IPO event. Ex-ante uncertainty is measured as the volatility in wage growth in each county, computed as the sum of the variances and covariance of the wage growth rate in the various industry sectors, weighted by the employment share of each individual sector. $High\ Ex-ante\ Uncertainty$ is an indicator variable that equals 1 if a county-year has wage growth volatility in the highest quartile of wage growth volatility across all county-years. Control variables include the following three variables. $Log\ Income\ Per\ Capita$ is the log of income per capita at the county-year level. $Log\ Population$ is the log number of population at the county-year level. $Log\ Num\ Pub\ Firm$ is the log number of public listed firms in the state. Column (1) pools sample from all county-years. Column (2) only pools sample from county-years that have wage growth volatility in the highest and lowest quartiles. Standard errors clustered at the state level are reported in parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table 9. Edgar Searches and New Business Registrations

Panel A. Edgar Downloads on Post IPO

	(1) Log(1+sum all)	(2) Log(1+sum S1)	(3) Log(1+sum 10K)
Post IPO	0.1065**	0.1896***	0.2144***
	(0.0534)	(0.0644)	(0.0602)
Observations	49,091	49,091	49,091
Controls	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes
Adj. R-squared	0.852	0.790	0.834

Panel B. New Business Registration in Counties with High S1/10K/10Q Download

	(1) Log(1+New Bus Reg)	(2) Log(1+New Bus Reg)
High S1	0.4504***	0.4392***
	(0.1058)	(0.1061)
High 10K	0.0138	0.0072
	(0.1208)	(0.1212)
Observations	49,091	49,091
Controls	Yes	Yes
Year-Quarter F.E.	No	Yes
Adjusted R-squared	0.515	0.518

Panel C. New Business Registration on Post IPO in counties with High S1/10K/10Q downloads

	(1) Log(1+New Bus Reg)	(2) Log(New Bus Reg)
Post IPO	0.1578**	0.0618
	(0.0764)	(0.0652)
Post IPO*High S1	0.2366*	0.3135***
	(0.1233)	(0.1057)
Post IPO*High 10K	-0.0154	0.1949**
	(0.1198)	(0.0855)
Observations	49,091	44,304
Controls	Yes	Yes
Year-Quarter F.E.	Yes	Yes
County F.E.	Yes	Yes
Cluster	County	County
Adjusted R-squared	0.953	0.955

Notes: Panel A presents results from regressing the log number of Edgar downloads on Post IPO at the country-quarter level. The sample period is from 2005 to 2016 as the Edgar data is available in this period. Specifically, in Column (1) *Log(1+sum all)* is defined as the log of one plus the total number of Edgar downloads across all file types. In Columns (2) through (4), *Log(1+sum S1)* and *Log(1+sum 10K)*, and *Log(1+sum 10Q)* are defined as log of one plus the total number of downloads across S1, 10K, and 10Q filings. In Panel B, the dependent variable is the log number of new businesses at the county-quarter level. *Post IPO 2* is a dummy variable equal to one for every county-quarter after the first IPO since 2005, 0 otherwise. In Panel B, *"High" S1, 10K, 10Q, All Other Filings* represent dummy variables equal to 1 if the total number of downloads for each respective filing type is above the median over the sample period, 0 otherwise. In Panel C, *"High" S1, 10K, 10Q, All Other Filings* represent dummy variables equal to 1 if the total number of downloads for each respective filing type is above the median over the sample period, 0 otherwise. For abbreviation, we include 10Q and All Other Filings as a control in Panel B and C. The sample is based on 8-quarters before vs. after the first IPO since 2005. The sample period spans the years 2005 through 2016. Standard errors clustered at the state level are reported in parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table 10. IPOs and Entrepreneurs' Edgar Searches

	(1) Log(1+Edgar Downloading Entrepreneurial Firms)	(2) Log(1+Entrepreneurial Downloads)
Post IPO	0.1619***	0.6637***
	(0.0409)	(0.2230)
Observations	11,700	11,700
Year F.E.	Yes	Yes
County F.E.	Yes	Yes
Cluster	County	County
Adjusted R-squared	0.857	0.792

Notes: This table reports the results of the regression of entrepreneurial Edgar downloading behavior on IPOs. The sample is the universe of US based CrunchBase companies. The dependent variable in Column (1) is the log number of CrunchBase firms that download at least one Edgar file in a county-year. Column (2) is the log total number of Edgar file downloaded in a county-year. Control variables include the following three variables. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the log number of population at the county-year level. Log Num Pub Firm is the log number of public listed firms in the state. Standard errors clustered at the county level are reported in the parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table 11. Entrepreneurial Outcomes

Panel A. Entrepreneurship Outcomes and Public Information Search

	(1) IPO	(2) Acquired	(3) Success
Edgar Download	0.2724***	0.1336***	0.2421***
	(0.0450)	(0.0330)	(0.0330)
Observations	227,310	227,310	227,310
Controls	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Adjusted R-squared	0.204	0.102	0.126

Notes: This table reports the results of the regression of entrepreneurial outcomes on the startup's Edgar search behavior. The sample is the universe of US based Crunchbase companies. The dependent variables are an IPO dummy (column 1), an indicator of market exit through acquisition (column 2), and an indicator of success (either IPO or being acquired). Edgar Download is an indicator variable that equals 1 if the company downloads at least 1 Edgar filing. Control variables include firm age and firm size (firm size is a categorical variable measured by the number of employees grouped into 10 bins provided by Crunchbase). Standard errors clustered at the county level are reported in the parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

ONLINE APPENDIX

Informing Entrepreneurs: Public Corporate Disclosure and New Business Formation

Table OA1. Spillover Effects of IPOs on New Business Registration

	(1) Log(1+New Bus Reg)	(2) Log(1+New Bus Reg)	(3) Log(1+New Bus Reg)
Post IPO	0.1720***		
	(0.0393)		
NCounty Post IPO		0.0892***	
		(0.0237)	
2NCounty Post IPO			0.0126
			(0.0273)
Observations	201,088	284,092	125,288
Controls	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes
Cluster	County	County	County
Adjusted R-squared	0.910	0.856	0.839

Notes: This table reports estimation of Model (1) that regresses the number of new business registrations on IPOs. Post IPO is an indicator variable that equals one if a county has had an IPO in the past, and zero otherwise. Columns (1) and (2) report the results of regressing new business registrations on Post IPO, excluding the IPO county's neighboring counties (Column (1)) and the IPO county but with the neighboring county (Column (2)), respectively. Column (3) excludes both the IPO neighboring counties and IPO counties. Specifically, 2NCounty Post IPO is an indicator variable that equals one if a the "second-degree" neighboring county has an IPO in the past, and zero otherwise. Control variables include the following three variables. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the log number of population at the county-year level. Log Num Pub Firm is the log number of public listed firms in the state. Standard errors clustered at the county level are reported in the parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table OA2. Public Firm Presence and Establishment Births

	(1) Log(1+Establishment Birth)	(2) Log(Establishment Birth)
Pub Firm Presence Quintile	0.0890*** (0.0096)	0.1030*** (0.0157)
Observations	782,850	552,868
Controls	Yes	Yes
Year F.E.	Yes	Yes
County F.E.	Yes	Yes
Industry F.E.	Yes	Yes
Cluster	County	County
Adjusted R-squared	0.784	0.795

Notes: This table reports the estimation results of a new model that regresses the number of new establishment births at the county, industry, year level on the quintile rank of public firm presence in the industry. Establishment Birth is the number of new establishments in an industry and county-year. Pub Firm Presence Quintile is the quintile rank of public firm presence taken from Shroff et al. (2017) and defined as and the number of public firms in an industry (3 digit SIC) divided by the total number firms in the industry, both public and private. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the number of population at the county-year level. Standard errors clustered at the county level are reported in the parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table OA3. Spinoffs vs. Private to Public IPOs

	(1) Log(1+New Bus Reg)	(2) Log(1+New Bus Reg)
Post Public IPO	0.1108	
	(0.1007)	
Post Private IPO		0.2715**
		(0.1276)
Observations	298,128	298,128
Control	Yes	Yes
Year-Quarter F.E.	Yes	Yes
County F.E.	Yes	Yes
Cluster	County	County
Adjusted R-squared	0.863	0.863

Notes: This table reports estimation of Model (1) that regress new business registrations on two types of IPOs. Post Public IPO as an indicator variable that is set to one in county quarters after a subsidiary of an already public firm goes public. In contrast, Post Private IPO is defined based on the IPOs of private firms that go public. Control variables include the following three variables. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the log number of population at the county-year level. Log Num Pub Firm is the log number of public listed firms in the state. Standard errors clustered at the state level are reported in the parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table OA4. Subsequent IPOs and Establishment Births

	(1) Log(1+Establishment Birth)	(2) Log(1+Establishment Birth)
Post Second Same Industry IPO	0.0122 (0.0074)	
Post Second Different Industry IPO		0.0235*** (0.0056)
Observations	866,359	866,359
Controls	Yes	Yes
Year F.E.	Yes	Yes
County F.E.	Yes	Yes
Industry F.E	Yes	Yes
Cluster	County	County
Adjusted R-squared	0.781	0.781

Notes: This table reports estimation of Model (1) that regresses establishment birth on two types of IPOs. Post Second Same/Industry IPO variable is constructed using NAICS classifications for industries. The timeframe for the dataset is from 2000 to 2015. We first record the first ever IPO in the county and its industry. If the county never had an IPO, both Post Second Same Industry IPO and Post Second Different Industry IPO remain 0. Next, if we find another IPO that is subsequent to the first IPO and is in the same NAICS industry, Post Second Same Industry IPO becomes 1; If we find another IPO that is subsequent to the first IPO and is in a different NAICS industry, Post Second Different Industry IPO becomes 1; if the county never had a second IPO, both dummy variables remain 0. For Establishment Birth, we used three fixed effects — County, Year, and Industry by NAICS — and clustered on County. For New Business Registration, we used two fixed effects — County and Year — and clustered on County. Control variables include the following three variables. Log Income Per Capita is the log of income per capita at the county-year level. Log Population is the log number of population at the county-year level. Log Num Pub Firm is the log number of public listed firms in the state. Standard errors clustered at the state level are reported in the parentheses. ***, **, and * mark statistical significance at 1%, 5%, and 10%, respectively.

Table OA5. Descriptive Statistics of Information Acquisition and Entrepreneur Financing

Panel A. Information Acquisition

	Obs.	Mean	SD	Median
All	49,091	660.33	5606.90	6.00
S1	49,091	8.48	65.57	0.00
10K	49,091	124.98	869.60	0.00
10Q	49,091	78.44	679.13	0.00
Others	49,091	135.88	1121.37	1.00

Panel B: Entrepreneurial Information Acquisition

	Obs.	Mean	SD	Median
Log(1+Edgar Downloading Entrepreneurial Firms)	11,700	0.12	0.39	0
Log(1+Entrepreneurial Downloads)	11,700	0.45	1.53	0

Panel C. Entrepreneur Financing

	Obs.	Mean	SD	Median
SBA Loan Count	78,416	1.49	1.42	1.10
SBA Loan Value	78,416	9.93	6.45	12.94
VC Funding Count	66,352	0.09	0.43	0.00
VC Funding Value	66,352	0.94	3.76	0.00

Notes: This table presents summary statistics for the sample of Edgar downloads (Panel A) from 2005 to 2016, entrepreneurial Edgar downloads (Panel B) from 2005 to 2016, and small business loan financing data (Panel C) from 1991 to 2016 obtained from the Small Business Administration and venture capital funding data from 1995 to 2016 obtained from Crunchbase. The sample is at the county-year level. In Panel A, All is defined as the total number of Edgar downloads across all file types, including 10K, 10Q, 8K, DEF 14A, S1 and others. S1, 10K, 10Q and Others are respectively defined as the total number of downloads of S1, 10K, 10Q and other filings (8K and DEF 14A). In Panel C, SBA Loan Count is defined as the number of loans issued in a year, and SBA Loan Value is defined as the total sum of loan values in the year. VC Funding Count is the number of VC investments in a year, and VC Funding Value is the total sum of VC investments in a year. VC investments include seed-round and series A through J investments. Standard errors clustered at the county level are reported in the parentheses.