Organization capital, large startups, and the dearth of IPOs*

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ABSTRACT

Many startups in the 2000s have remained private after achieving large valuations, a pattern that funding availability alone cannot explain. We propose that startups relying heavily on organization capital to achieve economies of scale and network effects through digital technologies are more likely to become large private firms than exit earlier via an IPO or acquisition. Using LinkedIn data, we construct a novel measure of organization capital intensity for startups. Exploiting a legal shock that strengthened organization capital protection, we provide causal evidence that organization-capital-intensive startups are more likely to remain private and grow large rather than exit early.

JEL codes: G24; G32; G34

Keywords: Startup; Organization Capital; Knowledge Capital; Economies of Scale; Network Effects; Venture Capital; IPO; Private vs. Public.

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The Globe.com was the Initial Public Offering (IPO) with the highest first-day return in 1998, yet its market capitalization at the offering price was only $88.2 million.[f] Though such small IPOs were common in the 1990s, they have almost disappeared, and their decrease has been examined extensively. However, since the Global Financial Crisis (GFC), many startups have reached private market valuations far exceeding the public market valuation of The Globe.com at its IPO instead of having an IPO or being acquired. We refer to these firms as large startups, defined as startups that reach a headline valuation exceeding $300 million in a private funding round. Though a well-documented increase in the funding available in private markets makes it possible for large startups to stay private (de Fontenay, 2017; Ewens and Farre-Mensa, 2020; de Fontenay and Rauterberg, 2021; Ewens and Farre-Mensa, 2022), abundant funding does not explain why some startups shun public markets and become large while staying private. For such startups to stay private, their value must be higher as private firms or their founders and investors must value private status for reasons other than wanting to maximize the startups' valuations. Hence, an abundance of funding in private markets is a necessary but not sufficient condition for large startups to stay private.

We propose and test an explanation for why some startups are better off remaining private and becoming large in private markets based on the composition of their capital. Specifically, we show that organization capital plays a causal role in explaining why startups grow large while staying private. A growing literature emphasizes the importance of organization capital (e.g., Lev and Radhakrishnan, 2005; Hulten and Hao, 2008; Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017). We argue that the information and communication technologies (ICT) revolution led to the emergence of a new type of firm that became more important over time. This type of firm relies heavily on organization capital to exploit economies of scale and network effects through internet and digital technologies. Though there is no commonly accepted definition of organization capital, many existing definitions, starting with Prescott and Visscher (1980), have in common that organization capital consists of firm-specific knowledge that

[f] See Joe Weisenthal and Tracy Alloway, Markets Odd Lots, "Transcript: The Globe.com co-founder on what a bubble bursting feels like."

enhances the productive efficiency of firms. This definition is too narrow in the sense that, for many firms for which organization capital is especially important, it is hard to distinguish between organization capital and the product. For instance, in 2025, NVIDIA's tangible capital is less than 1% of its market capitalization. Its CEO states that "NVIDIA's CUDA ecosystem is ultimately its great treasure."[g] Arguably, NVIDIA's organization capital is the core asset that is responsible for the creation, functioning, and growth of this ecosystem. We call organization capital firm-specific know-how embedded in people, processes, and routines used to improve productivity, support the development, functioning, and use of products, and create and expand markets for products.

Broadly speaking, building organization capital includes spending on management practices (Bloom and Van Reenen, 2007), corporate culture (Schein, 2010; Guiso, Sapienza, and Zingales, 2015; Graham et al., 2022), customer capital (He, Mostrom, and Sufi, 2024), information technology (Brynjolfsson, Hitt, and Yang, 2002), human capital (Prescott and Visscher, 1980; Eisfeldt and Papanikolaou, 2013; Zingales, 2000; Rajan and Zingales, 2000), relational contracts (Baker, Gibbons, and Murphy, 2002), firm leadership (Dessein and Prat, 2022), and firm capabilities (Teece, Pisano, and Shuen, 1997). Existing empirical evidence shows that, in the cross-section, average investment in organization capital in the 2000s exceeds the sum of average investment in R&D and capital expenditures (e.g., Enache and Srivastava, 2018). Atkeson and Kehoe (2005) show that the rents accruing to firm owners in manufacturing from organization capital are substantial. As discussed in Brynjolfsson, Hitt, and Yang (2002), the IT revolution enhanced the gains from investments in organization capital, as such investments are required to take advantage of computers, the internet, and digitalization.

Early in their lifecycle, the prospects of organization-capital-intensive startups are difficult to evaluate and monitor without concentrated ownership and specialized knowledge. Prior research shows that organization capital is fragile in young public firms (Boguth, Newton, and Simutin, 2022) and declines even in established firms following CEO turnover (Cai, Prat, and Yu, 2026). Relatedly, Baron and Hannan

[g] Dwarkesh Podcast, Jensen Huang, April 15, 2026.

(2002), using a large sample of startups, state that "companies in our sample that confronted higher turnover in a given period experienced significantly slower revenue growth in the ensuing two years." This evidence suggests that organization capital is likely even more fragile in startups that are still building the key components of organization capital required to exploit economies of scale and network effects. Moreover, their accounting performance appears weak because investments in organization capital are expensed rather than capitalized, making traditional financial statements poor indicators of their prospects (Lev, 2001; Ayyagari, Demirgüç-Kunt, and Maksimovic, 2024). These firms become highly valuable if they succeed in scaling, but have little residual value if they fail, since organization capital typically has low or zero liquidation value.

An example of a startup for which our conjecture applies is Uber. It was founded in 2009 but went public only in 2019. When it went public, analysts focused on its network effects and global strength. For instance, Deutsche Bank's initiation report stated that "strong market share with global presence warrants a premium valuation."[h] It was not yet profitable as it was still investing heavily in customer and driver acquisition, but a path to profitability was viewed as credible. Yet Uber at the time of the IPO had almost no property, plant, and equipment ($1.3 billion out of $24.4 billion of assets) and almost no intangible assets on its balance sheet ($0.08 billion). Its value instead reflected network effects that could be harvested once the firm operated at sufficient scale using the internet and digital technologies. Reaching that stage where ride sharing was accepted and legitimate required substantial investments in organization capital to overcome determined resistance from incumbent transportation providers across markets and to operate efficiently in the presence of such network effects.

Peters and Taylor (2017) distinguish between organization capital and knowledge capital, where knowledge capital is accumulated through R&D investments. Our explanation for why large organization-capital-intensive startups shun public markets does not apply to knowledge-capital-intensive startups. Unlike most forms of organization capital, knowledge capital can often be patented and frequently has

[h] Uber Technologies, Inc, Initiation of Coverage, Deutsche Bank, June 4, 2019.

stand-alone value (e.g., Mann, 2018). Startups with business models centered on developing knowledge capital may increase their value through an early trade sale if being acquired enables them to develop and market the product of that knowledge capital faster and more effectively (Gao, Ritter, and Zhu, 2013). By contrast, early trade sales are less likely to be value-maximizing for organization-capital-intensive startups that rely on economies of scale and network effects. Such startups are unlikely to benefit from an acquirer's existing distribution channels and are more likely to offer products or services that disrupt incumbents' business models. Crouzet, He, Lyonnet, and Ma (2025) show that established firms may find it optimal to reject new ideas that require a different organizational style. As a result, an early integration of such a startup into a larger firm is more likely to destroy value by disrupting the buildup of its organization capital and leading to employee turnover.

To investigate our explanation for why some startups become large instead of exiting and remain private even after they have become large, we create a unique startup database. We collect information on the 7,234 startups that received at least $50 million of venture capital (VC) funding from 2010 to 2024. We classify startups as large when they exceed a headline valuation of $300 million in a private funding round. A $300 million threshold ensures that the reasons for the decrease in IPOs for small startups, such as a potential increase in the fixed costs of being public, Sarbanes-Oxley, and the degradation of the market ecosystem, have limited or no relevance for our study (e.g., Gao, Ritter, and Zhu, 2013; Rose and Solomon, 2016).[i] Although some studies of startup exits have focused on manufacturing firms because of richer data (Chemmanur et al., 2025), few large startups are in manufacturing (12.7% of our large startups), suggesting that their results may not generalize to our sample. We find that 55% of large startups have a business model that uses the internet as the main delivery mechanism, while only 43% of all startups do so. This evidence is supportive of the role of digital technology for large startups.

[i] Gao, Ritter, and Zhu (2013) examine the decrease in small IPOs, where they define a small IPO as the IPO of a startup with less than $50 million of sales. Average sales in our sample of large startups is $200 million. Almost half of our large startup IPOs have a market capitalization at the offering of more than $1 billion.

To conduct our study, we must measure the organization capital intensity of startups. Existing approaches to measure organization capital use accounting data. Such data are not typically available for startups. We therefore introduce a new approach to measure the organization capital intensity of startups. We use LinkedIn data from Revelio Labs to classify employees who post on LinkedIn by their reported roles. The Revelio Labs data has been used in the literature to investigate firms' workforce exposure to specific activities and technologies. For instance, Eisfeldt, Schubert, and Zhang (2025) use that data to examine firms' exposure to AI. We define "organization capital employees" as those in roles that primarily involve the development and application of firm-specific know-how. This group includes selected managerial positions (e.g., product managers), technical and engineering roles (e.g., software engineers, IT specialists, system architects), and creative positions (e.g., product design). We measure organization capital intensity as the ratio of a startup's organization capital employees to the startup's total number of employees on LinkedIn and obtain a time-series of organization capital intensity for each startup in our sample. Using this measure, we show that organization capital intensity is systematically higher for startups that become large.

We also provide supporting evidence using the most widely used approach for estimating organization capital for public firms, which capitalizes the portion of SG&A expenses (net of R&D expenses) corresponding to investment in organization capital (e.g., Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017; Ewens, Peters, and Wang, 2024). The approach requires balance sheet data and income statement data that are not generally available for startups. We therefore proxy the organization capital intensity of startups with the organization capital intensity of young public firms in the industry of the startup. Under this approach, we define organization capital intensity as the ratio of organization capital divided by the sum of organization capital, capitalized R&D expenditures, and tangible capital. Using data on the organization capital intensity of young public firms, we find strong evidence that large startups are concentrated in industries with greater organization capital intensity.

We first provide causal evidence that strengthening legal protection for unpatentable intangible assets increases organization capital investment and the likelihood that startups become large and remain private.

We use the adoption of the federal Defend Trade Secrets Act (DTSA) of 2016 in combination with state-level variation in the enforcement of non-compete agreements and data on the composition of employees for startups obtained from LinkedIn. The DTSA increased firms' ability to protect their unpatentable intangible assets, including organization capital, by allowing firms to file civil lawsuits in federal courts, regardless of state laws.[j]

The passage of the DTSA has two testable implications. First, improved protection of organization capital should increase the organization capital intensity of startups and young public firms, as stronger legal protection raises the expected return to investments in organization capital, with a stronger effect in states with weak non-compete enforcement that provide little protection prior to the DTSA. Second, startups in those states should become more likely to reach large startup status, particularly those with a high proportion of organization capital employees before the adoption of the law. We find support for both conjectures. The passage of the law increased organization capital intensity of both startups and young public firms. Furthermore, startups with a high proportion of organization capital employees in weak enforcement states before the adoption of the law experience a significant increase in the probability of becoming large startups.

While the DTSA results demonstrate that organization capital intensity increases following the shock and that startups are more likely to achieve large startup status, particularly those with high ex ante organization capital employees, these reduced-form results do not establish a direct causal link from organization capital to large status. To address this identification challenge and establish a direct causal link, we employ a two-stage IV approach. Specifically, we exploit the DTSA shock and instrument organization capital intensity with the interaction of an industry's pre-2016 geographic footprint across weak non-compete agreement (NCA) enforcement states and an indicator for the post-2016Q2 period

[j] Khusnulgatin (2024) shows that the adoption of the DTSA and the staggered state-level adoption of the Uniform Trade Secrets Act (UTSA) increased firm age at the IPO. In contrast, we do not focus on the time it takes for firms to go public, but rather on whether startups are more likely to become large and more organization-capital-intensive.

following the DTSA. We find that there is a strong causal effect of organization capital intensity on the likelihood that a startup becomes large while private.

A separate identification concern is that industries that are more organization-capital-intensive may also be more attractive to investors and therefore benefit from a greater funding supply. To address this concern, we further instrument industry private market flows using state aggregate pension fund contributions. When we instrument both organization capital intensity and investor fund flows in regressions of a large private startup indicator on explanatory variables, we find that the coefficient on instrumented organization capital intensity is positive, large, and highly significant. The instrumented fund flows coefficient is positive and weakly significant in some, but not all specifications.

A key implication of our explanation is that startups that become large are more likely to have adopted business models that benefit from economies of scale and network effects. We find, using a new measure of the importance of scale and network effects in a startup's business model, that startups with business models designed to benefit from these effects are more likely to grow large remaining private rather than have an earlier exit.

A potential alternative explanation for why startups stay private after having become large is because their valuation in private markets is too high to justify going public. For instance, Cogman and Lau (2016) and others argue that valuations may be more generous in private markets than in public markets. Investors in private markets cannot sell short. If heterogeneity of expectations among potential investors is important, the most optimistic investors may determine the value of a startup in private markets. In addition, an IPO at a lower public valuation than the most recent headline private valuation can cause transfers among investor classes and may also be a bad signal for the market. We use market-to-book as our valuation measure for equity. We compute a *private market* market-to-book ratio (private market MB from now on) that, under some assumptions, is the lower bound of the market-to-book ratio for the private firm. We find that the likelihood that a startup becomes large does not increase with its private market MB. This evidence is inconsistent with the view that high valuations cause startups to stay private longer because of the difficulty of getting a better valuation in an IPO.

After focusing on the likelihood of startups becoming large, we provide evidence on the determinants of the likelihood of exit. We show, using Cox models, that organization-capital-intensive startups are less likely to exit. Further, startups that rely more on economies of scale and network effects exit later. Our results on the role of organization capital intensity in the timing of exit hold when we control for potential selection effects.

We provide additional support for our explanation using a sample of startups that go public. For those startups, we can obtain firm-level accounting data and governance characteristics. We compare large startups that go public with matched control startups that also go public and, prior to the large startup's qualifying round, had similar observable characteristics. We show that large startups invest less in R&D and more in organization capital than matched controls.

We also use the IPO data to investigate another alternative explanation, which we call the founder agency costs explanation. Ewens and Farre-Mensa (2020) provide evidence supporting the hypothesis that increased availability of funding enables founders to keep their startup private because they have more bargaining power. They make the case that founders want their startup to stay private because they can enjoy private benefits they could not enjoy if their startups were public. Note that if the startup stays private for founders to enjoy private benefits, it must be that staying private is suboptimal for investors since the consumption of private benefits comes at the expense of the investors.[k] Using dual-class share structures at the IPO as a proxy for founder power (Aggarwal, et al., 2022; Field and Lowry, 2022), we find that large startups choosing a dual-class structure go public at a higher valuation, do not have worse performance at the IPO, have more organization capital, more assets, more sales, and greater gross profits. This evidence seems hard to reconcile with the founder agency costs explanation for startups to choose to be large rather than exit early.

[k] If the startup stays private because doing so creates more value and founders appropriate part of this additional value through private benefits, then the investors will be better off because additional value is created for them. As a result, the reason the startup stays private is not private benefits for founders but the additional value created.

The paper proceeds as follows. In Section 1, we present a conceptual framework and introduce hypotheses that we use to test our main explanation for why large startups shun public markets. In Section 2, we describe our sample and investigate outcomes for large and non-large startups in our sample. In Section 3, we show how the distribution of startups and large startups differs across industries with different levels of organization capital intensity. In Section 4, we provide causal evidence for the role of organization capital. In Section 5, we test our prediction that organization-capital-intensive startups are more likely to become large startups rather than exit early. In Section 6, we use Cox proportional hazard regressions to estimate how organization capital intensity relates to the hazard of exit through an M&A transaction or listing. In Section 7, we provide support for our explanation for why some startups choose to become large rather than exit early using IPO data. We conclude in Section 8.

1. Conceptual framework and hypotheses development

In this section, we develop a conceptual framework to explain why some venture-backed startups become large while remaining private rather than exiting earlier through an IPO or a trade sale.[1] The central idea is that startups whose business models rely heavily on organization capital—firm-specific know-how embedded in people, processes, and routines—to take advantage of economies of scale and network effects through the use of the internet and digital technologies may rationally delay exit while building scale and network effects. We use this framework to distinguish our explanation from alternative explanations based on founder agency conflicts or private-market overvaluation and to derive testable predictions.

1.1. Remaining private as an operating, value-maximizing decision

Remaining private is potentially costly because it limits liquidity and often entails a higher cost of capital. A startup will therefore choose to remain private only if doing so improves future cash flows relative

[1] We are not the first to study the decision of private firms to exit (for recent reviews, see for instance, Da Rin, Hellmann, and Puri, 2013; Lowry, Michaely, and Volkova, 2017). However, to our knowledge, we are the first to focus on why some startups become large rather than exit and on the role of the composition of capital for these startups.

to an earlier exit and if it can obtain the funding to stay private. In our setting, this improvement takes the form of a higher likelihood that the firm successfully develops and scales its business model. We assume that funding is abundant in private markets so that firms that can improve future cash flows by staying private will be funded.

1.2. Organization capital, economies of scale, and network effects

Many organization-capital-intensive startups rely on economies of scale and network effects, often through digital or platform-based business models. These firms typically have few tangible assets, so they do not have collateral that mitigates risk for investors. For these firms, value creation depends critically on reaching sufficient scale. Before that point, organization-capital assets are fragile, uncertainty about execution is high, and the startup has little or no value if it does not succeed in scaling. Remaining private allows firms to concentrate ownership and monitoring, reduce employee turnover risk, limit disclosure, and focus managerial attention on execution, thereby increasing the probability of successfully reaching scale. This logic implies that startups whose value creation depends on organization capital and scale are more likely to delay exit until their organizational assets are sufficiently developed.

Three mechanisms reinforce the advantage of remaining private for organization-capital-intensive startups. First, investments in organization capital are difficult to assess and monitor for public market investors, in part because these investments are expensed and not capitalized, as long as the startup has not reached scale, which makes concentrated, informed monitoring in private markets more valuable. Second, public disclosures increase the risk of imitation, whereas remaining private helps firms to build scale and establish robust network effects before exposing their business model fully to competitors (e.g., Breuer, Leuz, and Vanhaverbeke, 2025). Third, organization capital is partly embedded in employees (Eisfeldt and Papanikolaou, 2013; Bolton, Wang, and Yang, 2019; Dou, et al., 2021), and early public status increases labor-market visibility and turnover risk (Babina, Ouimet, and Zarutskie, 2025; Bias, 2024; Bias et al., 2026) at a stage when the departure of key personnel can destroy firm value, possibly even the firm.

Rajan (2012) emphasizes the importance of standardization for a startup to be able to tap public markets. His point is that the startup should be able to thrive without critical inputs from existing key talents. Standardization is not possible unless much uncertainty has been resolved: the startup must have reached a level of maturity that enables it to produce the output it set out to produce at the level it expected to produce. Bias et al. (2026) provide empirical evidence showing that firms become more hierarchical and standardized around IPOs. Since key talents play an especially critical role in the buildup of organization capital, startups that rely more on organization capital for their business model are likely to stay private longer as it will take them longer to reach a point where they can thrive without these key talents.

1.3. Organization capital vs knowledge capital

The framework applies specifically to organization capital and not to all forms of intangible capital. Knowledge capital accumulated through R&D is often patentable and has stand-alone value. This knowledge is typically geared to new products that must be commercialized, making early exit through acquisition more attractive. [m] In contrast, organization capital is tightly linked to the firm's internal structure and processes, so that it may suffer from loss of value in an acquisition where the organization capital is integrated in a larger organization. As a result, organization-capital-intensive startups are less likely to benefit from early trade sales and more likely to delay exit.

1.4. Alternative explanations

Two alternative explanations for delayed exit are founder agency and private-market overvaluation. Founder agency predicts that delayed IPOs reflect founders' preferences for control and private benefits and should be associated with weaker outcomes (Ewens and Farre-Mensa, 2020). Overvaluation predicts that firms remain private because public markets cannot sustain private valuations. In contrast, our framework predicts that delayed exit is value maximizing for organization-capital-intensive startups and

[m] For instance, a startup may benefit from being acquired by a larger company with established sales channels (Gans, Hsu, and Stern, 2002).

driven by real operating considerations rather than because of founder preferences or higher private valuations.

1.5. Testable predictions

Our framework yields the following testable predictions:

1. Startups with higher organization capital intensity that rely on economies of scale and network effects are more likely to become large while remaining private.
2. Exogenous enhancements in the protection of organization capital increase investment in organization capital and the likelihood of becoming large while remaining private.
3. Organization-capital-intensive startups are less likely to exit early than other startups.
4. Large startups are more likely to exit through IPOs compared to startups in general.
5. Delayed exit among organization-capital-intensive startups is not explained by higher private-market valuations or founder agency conflicts.

2. Large startups over time

In this section, we explain how we construct our sample of large startups. We provide summary statistics for our sample and show how these statistics differ by a startup's classification as large or small. We then show how the number of large startups evolves over time.

2.1. Sample construction

Our main data provider is CB Insights. We start by compiling a list of U.S. startups from CB Insights that took money from VCs and had at least $50 million of total funding (cumulatively across all available rounds) between Q1 2010 and Q4 2024. We exclude startups that were incorporated before 2000. We track the startups through time. From this sample, we form our sample of large startups. That sample includes all startups that have crossed the threshold of $300 million post-money headline valuation as a private firm. A startup is included in the large startup sample from the time it crosses the threshold.[n] For simplicity, we call the startups that have not crossed the threshold small startups. CB Insights classifies each VC-funded startup into one of 20 sectors. It classifies startups as belonging to the internet sector if their business depends on a delivery mode that uses the internet. With this classification, 55% of large startups and 43% of all startups are in the internet sector. This evidence shows that digital technology is important for large startups. To understand the type of product that a startup sells, we reclassify startups that CB Insights includes in the internet sector according to the type of goods or services they provide. When we refer to the sector or industry of a startup, we use the sector or industry defined by the type of goods or services.

We introduce a variable that measures the importance of scale in the business plan of the startup. The variable *Scale* takes a value of one if the description of a startup's business in CB Insights includes one of the words "platform," "network," or "connect."[o]

We obtain data for startup exits from SDC Platinum, CB Insights, Standard and Poor's (S&P) Capital IQ, and individual web searches. We also use the list of venture-capital-backed IPOs compiled by Jay Ritter.[p] We distinguish between five different types of exits—direct listings (DLs), initial public offerings (IPOs), reverse mergers through special purpose acquisition companies (SPACs), M&As, and failures. We classify a large startup as having failed if it declares bankruptcy or is acquired for less than 25% of the large startup round post-money headline valuation. For direct listings and IPOs, the exit date is the offer date. The exit date for reverse mergers and M&As is the deal completion date. We also record whether a startup has a down round, defined as a funding round with a post-money headline valuation of less than its largest headline valuation.

[n] We use the $300 million threshold as an indicator of success, not as an accurate valuation. True valuations may be less than headline valuations because the most recent investors may receive benefits that earlier investors do not (Gornall and Strebulaev, 2020). Imbierowicz and Rauch (2024) show that investors value shares with different rights differently. It would not be feasible to measure true valuations for a sample of our size. However, for our purpose, using the headline valuations is not problematic.

[o] An existing approach in the literature is to look at the IPO prospectus to obtain information about scaling (Somaya and You, 2024). The advantage of our approach is that it can be used for all startups in our sample, whether they go public or not.

[p] Available for download free of charge from https://site.warrington.ufl.edu/ritter/ipo-data/.

In some of our analyses, we use industry averages of accounting characteristics of young publicly listed firms as independent variables. The variables are defined in the Appendix. We define young firms in an industry as the firms in the bottom quartile of the age distribution. The data on public firm accounting characteristics comes from Standard & Poor's Compustat database.

We obtain data on startup employees' employment history and skills since 2010 from Revelio Labs, which aggregates data from LinkedIn profiles. LinkedIn is the leading professional networking platform in the U.S. and has the most comprehensive data about firms' workforce composition. An important advantage of their data is its coverage of private firms, which enables us to construct measures of organization capital intensity for our sample startups. LinkedIn adoption rates are highest among young, educated workers in technology and professional service sectors (Zhu, Fritzler, and Orlowski, 2018). Therefore, we expect the LinkedIn data to provide good coverage of the employees of our sample startups. While our measure captures only the human capital component of organization capital, the granularity of the data enables us to measure this dimension with high precision at the startup level. We have data for 88% of the startups in our sample of startups that received at least $50 million of cumulative VC funding between Q1 2010 and Q4 2024.

Following the literature on organization capital (Evenson and Westphal, 1995; Brynjolfsson, Hitt, and Yang, 2002; Corrado and Hulten, 2010; Eisfeldt and Papanikolaou, 2013; He, Mostrom, and Sufi, 2024), we identify "organization capital employees" as those in roles that primarily involve the development and application of firm-specific knowledge and processes. The roles include managerial positions that coordinate production processes (e.g., product managers), technical roles that build information technology systems and institutional knowledge (e.g., software engineers, IT specialists, system architects), and creative roles that contribute to customer capital and brand development (e.g., product design).

2.2. Organization capital and organization capital intensity

Organization capital plays a central role in our explanation for why startups stay private. We use two approaches to measure organization capital intensity, one based on the LinkedIn data described in the previous section and one based on capitalized SG&A expenses. The measure based on the LinkedIn data is new to the literature.[q] For that measure, we define organization capital intensity at the startup level with the share of organization capital employees, i.e., the number of organization capital employees divided by the total number of employees at a point in time. The measure captures the extent to which a startup's workforce in a given quarter is concentrated in roles that build and maintain firm-specific knowledge and processes. A higher share indicates greater reliance on organization capital. Section A in the Internet Appendix provides more details on our approach and validation exercises.

The second measure has been used extensively in the literature. For that measure, we start from SG&A expenses. SG&A expenses net of R&D expenditures (or a fraction thereof) is used as a proxy for investment in organization capital (Peters and Taylor, 2017). However, since SG&A expenses are a flow variable, we adapt the approach from Ewens, Peters, and Wang (2024). For each firm, we apply a perpetual inventory method to capitalize the fraction of SG&A expenditures net of R&D expenditures starting from the firm's first quarter in Compustat, with the stock initialized at zero. We proceed in the same way with R&D expenditures to estimate knowledge capital, and with capital expenditures to construct tangible capital. We capitalize capital expenditures (CAPEX) rather than using gross PP&E to estimate tangible capital because our sample consists of young public firms. Gross PP&E would reflect tangible assets acquired while firms were still private, and no comparable pre-IPO measure of organization or knowledge capital is available. Capitalizing CAPEX from each firm's first quarter in Compustat ensures the three capital stocks are constructed on the same footing. We obtain industry-specific depreciation rates for R&D, and industry-specific fractions of SG&A expenditures contributing to investment in organization capital from Ewens, Peters, and Wang (2024).[r] As in Ewens, Peters, and Wang (2024), we use an annual depreciation rate of 20% for SG&A. We apply a 10% annual depreciation rate for capital expenditures.

[q] Cai, Prat, and Yu (2026) use Glassdoor data to construct a measure of organization capital. With Glassdoor data, they can measure organization capital for startups as well. They extract their measures using text analysis. Their approach does not make it possible to construct the measure of organization capital intensity we need in our empirical work.

[r] We assume that the parameters estimated at the end of their sample period hold until the end of our sample period.

We do not have income statements including SG&A expenses and balance sheet data for startups. Instead, we proxy a startup's organization capital by the organization capital of young firms in the startup's industry. We measure organization capital intensity as the ratio of organization capital divided by the sum of knowledge capital, tangible capital, and organization capital, following Chun et al. (2008), who define IT intensity in this way. For startups that go public, we obtain SG&A expenditures from the IPO prospectus for the year before the startups go public. At the industry level, our LinkedIn-based measure for the organization capital intensity of startups is positively correlated with the measure of organization capital intensity based on the capitalization of SG&A expenses net of R&D expenditures for young public firms, with a pairwise correlation of 0.47 across industries.

2.3. The sample of large startups and organization capital

During our sample period, 7,234 VC-funded startups received funding of at least $50 million. Of these startups, 2,222 became large startups. Panel A of Table 1 describes the sample of startups. Columns (1) to (3) show statistics for all 7,234 startups. We can use LinkedIn data for 6,516 startups and find that the average organization capital intensity using the LinkedIn measure is 0.42. We also tabulate the average industry-based organization capital intensity, which is 0.43. Total equity funding is skewed as the mean is $198 million but the median is only $90 million. Private market MB is 2.78 on average. The post-money valuation (PMV) after the last private round is $690 million on average and $180 million at the median. Thirty-seven percent of startups exit but, consistent with Gao, Ritter, and Zhu (2013), only 26% of the exits are IPOs and 53% are M&A exits. Eleven percent of exits are failures. The average age at exit is 8 years. The *Scale* variable, which takes a value of one if the description of a startup's business in CB Insights includes one of the words "platform," "network," or "connect," has an average of 0.42. Finally, we tabulate the mean of an indicator variable that equals one if the startup headquarters is within two hundred miles of San Francisco, "Near San Francisco," to account for unique agglomeration benefits that potentially explain why so many startups are close to San Francisco. We find that 32% of sample startups are close to San Francisco.

We now compare large startups (Columns (4) and (5)) to small startups (Columns (6) and (7)). As expected, large startups have a higher share of organization capital employees than small startups (46% versus 40% for the mean for the LinkedIn measure and 45% versus 42% for the industry-based measure). Figure 1 shows that the frequency of small startups is higher for lower values of organization capital intensity. The frequency of large startups is higher for higher values of organization capital intensity, but the frequency of both types of startups converges for very high organization capital intensity. Large startups are substantially less likely to have very low organization capital intensities. Not surprisingly, large startups have more equity rounds, raise more equity, and have a higher PMV after the last private round than small startups. The average private market MB of large startups is 4.53, which is much higher than the average private market MB of 1.95 of small startups. A smaller fraction of small startups exit than of large startups. Strikingly, 63% of exiting small startups do so through M&A, while only 35% of exiting large startups do so. A large startup is almost twice as likely to use an IPO for exit than a small startup. Small startups are more likely to fail, but less likely to have a down round, than large startups. Large startups are more likely to have a business model that uses scale (49% vs 39%), and more of them are closer to San Francisco (40% vs 29%).

In Panel B of Table 1, we provide additional data for large startups. We show that it takes an average of six years and three equity rounds before a startup becomes a large startup. Large startups have an average of \$153 million of total funding before becoming a large startup and raise an average of \$370 million after becoming large and before exit. On average, large startups that exit do so 2.5 years after becoming large.

2.4. Births, exits, and growth of large startups

Figure 2 shows the evolution of the number of large startups over time. Panel A plots the number of startups passing the large startup threshold ("born" from now on) in each quarter of our sample period. The average number of births per quarter is 37. The highest number born in a quarter is 136 in the second quarter of 2021. The figure shows a high level of births starting in 2018 and ending in 2022. Panel B plots the number of large startups that exit per quarter. The average number of exits in a quarter is 16. The number of exits is very high from the second quarter of 2020 to the third quarter of 2021. The highest number of exits is 78 in the second quarter of 2021. There are only three quarters with more exits than births. These quarters are the third quarter of 2020, the second quarter of 2024, and the last quarter of the sample period. As seen in Panel C, the number of large startups in existence increases throughout our sample period, but the rate of increase becomes low after the second quarter of 2022.

Table 2 provides information on the 955 large startups that exit or have a down round during the sample period. We found 105 down rounds and 87 failures. The most important form of exit is an IPO. We find that 356 large startups exit through an IPO. The next most important form of exit is through a trade sale. A trade sale exit occurs for 336 startups. However, these numbers underestimate the extent to which going public is the most important form of exit. We also have 62 startups that exit through a de-SPAC transaction and 9 startups that exit through a direct listing. As a result, 427 large startups go public, which represents 45% of the exits.

IPO exits occur slightly later than M&A exits. The median IPO exit is 1.51 years after a startup becomes large, while the median time to an M&A exit is 1.16 years. The median PMV at exit for IPOs ($0.86 billion) is lower than for SPACs ($2.40 billion) or direct listings ($6.08 billion) but higher than for M&A exits ($0.51 billion). The startups that go public also receive more private funding than those that exit through M&A. We compute the ratio of PMV at exit relative to total equity funding, which we call the exit MB. We also report the private market MB, defined as the PMV for the last funding round before exit relative to total equity funding. A comparison of these two ratios allows us to understand whether the exit happened at a higher valuation than the last private funding round. We find that the median exit MB (private market MB) for an IPO is 4.14 (2.23), for a SPAC it is 5.36 (3.06), and for an M&A it is 3.86 (3.27). Therefore, the median exit MB is substantially larger than the median private market MB after the last private funding round for all types of successful exits. This fact is hard to reconcile with the overvaluation explanation.

Gao, Ritter, and Zhu (2013) investigate why there are so few IPOs in the 2000s. In their paper, they distinguish between small and large startups. They document a decrease in IPOs that is extremely large for small startups compared to other startups. They advance the explanation that due to changes in technology and goods markets, firms must be able to access markets more quickly and more extensively, which leads them to merge with firms that will facilitate that access (see also Chemmanur et al., 2025). In the 2000s, more than 80% of all non-failed exits are through a trade sale (Gao, Ritter, and Zhu, 2013; Broughman, Wansley, and Weinstein, 2025). Our evidence for large startups is very different. Only 44% of all non-failed exits by large startups are trade sales. With large startups, the most likely outcome is to go public. This evidence suggests that large startups are quite different from other startups and that the issues that have adversely affected the probability that a small private firm would have an IPO do not seem to affect the typical large startup.

3. Industry, large startup status, and organization capital

Figure 3 shows the distribution of organization capital, knowledge capital, and tangible capital intensities across sectors using data from all public firms. Because this sample is not restricted to young firms, we measure tangible capital using gross PP&E. The figure shows the distribution for the 2010s. In the 2010s, organization capital intensity is lowest in the energy and utilities sector and less than 20% in the environment, agriculture, and transportation sectors. It is highest with almost 80% in the risk & security sector and more than 50% in the internet, software, business products and services (business in the following), and media sectors. Knowledge capital intensity is highest in the healthcare sector with more than 70%, followed by the agriculture, computer, and electronics sectors. It is lowest and trivially small in the metals and mining, risk and security, retail, environment, leisure, and energy and utilities sectors.

Column (1) of Table 3 reports the number of large startups in each sector. In Column (2), we show the percentage of large startups in each sector. Large startups are concentrated in three sectors. The sector with the largest number of large startups is the business sector. It has 434 large startups, equivalent to 19.5% of all large startups. The healthcare sector has 414 large startups (18.6%). The internet sector comes in third, with 364 large startups (16.4%). The financial sector is the only other sector with more than 10% of large startups. The industrial sector which consists of manufacturing firms has only 5.2% of the large startups (adding the computer, consumer, and electronics sectors that also include manufacturing firms brings the percentage for manufacturing to 12.7%). Six sectors have less than 1% of the large startups each.

We compare the sectoral distribution of large startups with that of startups that raised more than $50 million (Columns (3) and (4)). The healthcare sector has the largest number of startups (2,047, or 28.3% of startups). The next most important sector is the business sector, with 1,073 firms, or 14.8% of startups. The internet sector has 913 startups (12.6%). The sector that is the most overweight among startups compared to large startups is the healthcare sector. It has 28.3% of startups but only 18.6% of large startups. In contrast, the business sector is the most underweight among startups compared to large startups. It has 14.8% of startups but 19.5% of large startups. While healthcare startups have a 20% probability of being large (414 / 2047), business, internet, and risk and security startups are tied for the highest probability of being large with a 40% probability.

We then map the 20 CB Insights sectors to 4-digit NAICS code industries so that we can make an industry comparison between large startups, publicly listed firms, and IPOs. Column (5) in Table 3 shows the number of public firms for each sector in our sample, and Column (6) shows the percentage of public firms in each sector. The healthcare sector has the largest number of startups and the second largest number of public firms in the sample. The sector with the most public firms, the financial sector, is underrepresented among startups and large startups. Seven sectors have more VC-funded startups than public firms. These sectors are risk and security, environment, agriculture, business, healthcare, mobile, and internet. Public firms are much less concentrated in sectors than VC-funded startups and large startups.

We further show in Columns (7) and (8) each sector's number and percentage of IPOs. The sector with the largest number of IPOs is healthcare, with 604 IPOs, followed by business with 583 IPOs, and electronics with 511.[s] These three sectors account for 47.4% of IPOs. Electronics has 14.3% of IPOs but only 1.6% of large startups. The internet sector has 0.7% of the IPOs but 16.4% of large startups.

[s] The large number of IPOs in the healthcare sector is likely, in part, the result of one of the few public disclosure requirements that apply to private companies. In 2007, Congress passed the Food and Drug Administration Amendments Act (FDAAA) that requires all companies (including private companies) to disclose publicly the results

With our explanation for why large startups stay private, we would expect the correlation between organization capital intensity and the percentage of large startups in a sector to be positive. It is 33%. We estimate the same correlation for the ratio of large startups to public firms and the ratio of large startups to IPOs in a sector. The former correlation is 58.9% and the latter is 39.9%. In other words, sectors with a higher organization capital intensity have more large startups, no matter whether we standardize the number of large startups by the number of startups, the number of public firms, or the number of IPOs. The standardized number of large startups increases with the degree of organization capital intensity of the sector.

4. Evidence from a shock to the return to investment in organization capital

Our hypotheses predict that shocks raising the return to organization capital increase such investment and the likelihood of organization-capital-intensive startups to grow large while remaining private.

We exploit the introduction of the Defend Trade Secrets Act (DTSA) of 2016, which provides a uniform federal cause of action for trade secret misappropriation, in conjunction with cross-state heterogeneity in non-compete agreement (NCA) enforceability. The DTSA increases the return to investments in organization capital as it improves the ability of firms to defend their organization capital through the legal process. The identifying variation arises from the differential marginal value of the DTSA across jurisdictions: firms in states with historically weak-NCA enforcement lacked strong legal instruments to prevent employee mobility and knowledge leakage and thus faced a higher risk in accumulating and retaining organization capital.[t] First, we show that the DTSA increases investment in organization capital by young publicly listed firms headquartered in weak enforcement states. Second, we show that the DTSA increases the share of organization capital employees of startups in weak-NCA enforcement states. Finally, we show that the DTSA increases the likelihood of startups becoming large in weak-NCA enforcement

of Phase II trials or above. As a result, firms in the biopharmaceutical industry that were private lost a disclosure advantage of being private, which led to an increase in IPOs from these firms (see Aghamolla and Thakor, 2022).

[t] Garmaise (2011) finds that NCAs promote executive stability.

states and that this effect is stronger for startups that have more organization capital employees before the DTSA.

We first estimate difference-in-differences (DiD) models of organization capital intensity on a sample of young public firms in Compustat using capitalized organization capital investments. We use this measure of organization capital intensity because we want to use a comparable measure for knowledge capital intensity. Our treatment variable is equal to 1 after the passage of DTSA for young firms headquartered in weak enforcement states. We assume that most employees in young firms work and live in the headquarter state and are thus bound by NCA enforceability in that state.[u] We use a time window from Q1 2011 to Q2 2021 around the DTSA treatment quarter of Q2 2016. We obtain data on the state-level NCA enforceability score from Golubov and Zhong (2024). The score ranges from zero to twelve, with zero indicating no enforcement of NCAs and higher scores indicating stronger enforcement. We classify the states with a below-median score before 2016 as having weak enforceability. Figure 4 shows there is substantial cross-state heterogeneity in NCA enforceability in the United States. This geographic variation in NCA enforceability supports our identification strategy.[v] Our baseline DiD specification is as follows:

$$\text{Organization capital intensity}_{ijst} = \alpha + \beta_1(\text{Weak Ex ante NCA}_s \times \text{Post DTSA}_t) + \mu_j + \delta_s + \gamma_t + \epsilon_{ijst} \quad (1)$$

where $\text{Weak Ex ante NCA}_s \times \text{Post DTSA}_t$ equals one for weak ex-ante NCA enforceability in state *s* after the enactment of the DTSA in Q2 2016. μ_j, δ_s, and γ_t are industry, state, and year-quarter fixed effects,

[u] This assumption is consistent with geographic clustering of entrepreneurial activity and startup labor markets (e.g., Zhu, Fritzler, and Orlowski, 2018). As a robustness check, we alternatively assign state exposure using employee-level location information from the LinkedIn data. The LinkedIn location variable reflects the most recently observed location rather than the historical location at the time of employment. Using this information as a proxy for employee location during employment at the startup yields similar results as those presented in Tables 4, 5, and 6. These robustness tests are reported in the Internet Appendix.

[v] Figure 1 in Golubov and Zhong (2024) lists the enforceability of NCAs across U.S. states in 2013. We use NCA enforceability as of 2013 because that is the last year in their sample. The main take-away for our study from their Figure 1 is that CA is an outlier, combining near-complete NCA non-enforcement with a dense VC and startup ecosystem. A concern is that the estimated DTSA effects could be driven by California-specific dynamics rather than by differential exposure to trade secret protection. The concern is mitigated by the presence of substantial startup activity in high-enforcement states such as MA and TX, and by the fact that all results are robust to excluding CA from the sample.

respectively. Because we focus on young public firms that are typically five years old or younger, we have limited within-firm variation and thus do not include firm fixed effects.

Table 4, Panel A shows estimates of the DiD regressions. In Column (1), we show that the organization capital intensity of young firms in weak enforcement states increases by 3.4 percentage points, a statistically and economically significant increase relative to the pre-treatment average organization capital intensity of 41%. Columns (2) and (3) estimate similar DiD regressions for knowledge capital intensity and tangible capital intensity and show that 88% of the increase in organization capital intensity comes at the expense of tangible capital intensity and 12% at the expense of knowledge capital intensity (those intensities add to one).

This difference-in-differences design identifies the causal impact of the DTSA through its uniform national implementation and by exploiting pre-existing cross-state variation in non-compete enforceability. The key identifying assumption of parallel pre-trends is plausible given the institutional stability of state-level NCA laws and the absence of simultaneous confounding shocks. While one potential threat is firm self-selection into strong-NCA states based on anticipated needs for protecting organization capital, this concern is mitigated by the fact that firm location decisions, particularly for early-stage private firms, are often driven by factors like labor markets, investor networks, and industry clusters, rather than legal regimes per se. Moreover, the DTSA introduces a meaningful legal shift for firms in weak-NCA states, which previously had weaker state-level protection for trade secrets through non-compete agreements, making the new uniform federal baseline differentially impactful and thereby generating cross-state variation in marginal benefit that is plausibly exogenous. We provide some evidence for the assumption that the trend in organization capital intensity would have evolved similarly absent treatment in Panel A of Figure 5. We plot the dynamic treatment effects during the estimation window. The figure shows that pre-treatment differences in organization capital intensity are statistically insignificant.

Roughly half of the startups are from California, so we want to make sure that our results are not due to changes taking place in California other than the shock we consider. We therefore conduct an additional robustness test where we remove startups based in California from the sample. The results are tabulated in Table IA.B.2 of the Internet Appendix. We find that our results hold without California in the sample.

Table 5 reports pre-treatment means of key observable characteristics for treated and control startups in Q4 2015. Treated startups are somewhat larger in terms of valuation and cumulative funding, and slightly older. Private market-to-book ratios are similar across the two groups. These differences in valuation, funding, and age motivate our propensity score matching procedure in Panels B and C of Table 4, which matches treated and control startups based on these ex ante characteristics.

Using our LinkedIn data, we can implement a difference-in-differences design to estimate the impact of the DTSA shock on the accumulation of organization capital by startups. We estimate regressions like those in Panel A of Table 4, but we now include startup fixed effects in place of industry and state fixed effects. We report in Panel B of Table 4 a strong increase in the startup-level measure of organization capital intensity based on the LinkedIn data following the DTSA shock. The results in Column (1) suggest that the share of organization capital employees of treated startups increases by 3 percentage points relative to control startups after the DTSA. We show further that our results are robust to allowing the accumulation of organization capital by startups to differ in the post-DTSA period based on pre-treatment characteristics such as cumulative funding, age, or headline valuations. The interactions do not have a noticeable impact on the coefficient for the shock. In Panel B of Figure 5, we show that there are no significant pre-trends that would threaten the parallel trends assumption.

We next turn to the DiD evidence for the treatment effect on the likelihood that a startup becomes a large startup. We first estimate the following regression:

$$\text{Large startup}_{ist} = \alpha + \beta_1(\text{Weak Ex ante NCA}_s \times \text{Post DTSA}_t) + \omega_i + \gamma_t + \epsilon_{ist} \qquad (2)$$

Including startup and year-quarter fixed effects controls for time-invariant unobserved firm heterogeneity and common shocks across startups in a quarter, allowing us to interpret the β_1 coefficient as the estimated average treatment effect on the treated (ATT) startups.

Panel C of Table 4 presents the DiD results from linear probability models of large startup status. Column (1) shows our baseline estimate of the treatment effect for large startups. We find that startups in states with weak-NCA enforcement are more likely to become large after the enactment of the DTSA than startups in states with stronger NCA enforcement. The treatment effect corresponds to a 6.6 percentage point increase in the likelihood of becoming large, a considerable increase relative to the 8% unconditional probability of being a large startup in the pre-treatment window. To the extent that greater protection of unpatentable intangible assets makes it more valuable for startups to build organization capital (Panel B), the results suggest organization capital is an important factor in startups choosing not to exit before achieving large status. Panel C of Figure 5 shows that there are no significant pre-trends.

We show further that our results are robust to allowing startup outcomes to differ in the post-DTSA period based on pre-treatment characteristics. Specifically, in Column (2), we control for the interaction of pre-DTSA cumulative funding of the startups and the *Post-DTSA* indicator. While we find that a startup with higher ex ante cumulative funding is more likely to become a large startup in the post period, the treatment effect is still positive and significant. We then control for the startup's age in Column (3). Age is not significant, and the coefficient on treatment is unaffected. Lastly, we control for the pre-DTSA headline valuation in Column (4). The headline valuation has a positive and significant coefficient, but the treatment effect is still positive and significant.

We next extend the analysis by exploiting heterogeneity in the importance of organization capital across startups. We use our measure of organization capital intensity for startups derived from LinkedIn data. This allows us to implement a triple-difference design that compares treated and control startups before and after the DTSA, with additional variation based on their reliance on organization capital employees. Specifically, we interact $\textit{Weak ex ante NCA}_s \times \textit{Post DTSA}_t$ with the startup's ex ante fraction of organization capital employees decile and include organization capital employees decile by year-quarter fixed effects.[w] These fixed effects flexibly control for differential trends across startups with varying levels of organization

[w] Note that these fixed effects subsume the *Organization capital employees decile* × *Post DTSA* interaction term.

capital intensity, ensuring that our results are not confounded by systematic differences in growth trajectories between high- and low-organization capital intensity firms.

Columns (5) and (6) of Panel C report the results. The interaction of weak-NCA enforcement with the fraction of organization capital employees and the post-DTSA indicator is positive and both statistically and economically significant. The results in Column (5) suggest that moving from the first to the last decile of the fraction of ex ante organization capital employees increases the likelihood of being a large startup by 14.4 percentage points after the DTSA, nearly doubling the probability relative to the 8% unconditional baseline in the pre-treatment window. The triple-difference results imply that the treatment effect is concentrated among startups that relied more heavily on organization capital employees prior to the DTSA. In other words, the positive impact of strong trade secrets protection on the likelihood of reaching large status is driven by firms for which organization capital was more important ex ante.

To the extent that greater protection of unpatentable intangible assets makes it more valuable for young public firms and startups to build organization capital as shown in Table 4, Panels A and B, the results of Panel C suggest organization capital is an important factor in startups choosing not to exit before achieving large status.

5. Business model, VC fund flows, private market valuations, and large startups

While the results in the previous section show that the DTSA shock increased both organization capital intensity and the likelihood of becoming a large startup, the DTSA reduced-form results do not directly establish a causal link from organization capital intensity to large startup status. Therefore, we now directly test whether organization capital intensity causally affects the probability of becoming a large startup. We focus on startup-level panel regressions where the dependent variable takes the value of one in quarter t if the startup becomes a large startup in quarter t and zero otherwise. We only include startups in the sample up to the quarter in which they become large. We then regress the dependent variable on lagged organization capital intensity and control for lagged funding availability, importance of scale and network effects for the business model, private market MB, the startup's age since incorporation, and its distance from San

Francisco. The startup's private market MB is the ratio of the most recent headline valuation divided by the total amount of funds raised up to the most recent valuation. We also construct an industry private market MB for the startup, which is the average of the private market MB for the startups in the industry other than the startup itself.

An endogeneity concern with this specification is that organization capital intensity is likely correlated with unobserved growth opportunities: startups and industries that appear more promising to investors may simultaneously accumulate more organization capital and be more likely to yield large startup outcomes. Therefore, regressing large startup status on organization capital intensity would confound the effect of organization capital with the effect of unobserved startup or industry potential.

To establish a direct causal link between organization capital intensity and large status, we exploit the DTSA shock and instrument organization capital intensity with the interaction of an industry's pre-2016 share of startups headquartered in weak-NCA enforcement states and an indicator for the post-2016Q2 period following the Defend Trade Secrets Act (DTSA). Formally,

$$Z^{\mathrm{Org}}{}_{j,t} = \text{Weak-NCA Exp}_{j,\,pre} \times 1_{t \geq \text{DTSA Q2 2016}}$$

where $\textit{Weak-NCA Exp}_{j,\,pre}$ is the share of industry *j's* pre-2016 startups located in states with historically weak non-compete enforcement. More specifically,

$$\text{Weak-NCA Exp}_{j,\,pre} = \frac{\sum_{s \in s_{\text{weak}}} \text{Startups}_{j,s,\,pre}}{\sum \text{Startups}_{j,s,\,pre}}$$

$\textit{Startups}_{j,s,\,pre}$ is the number of CB Insights-covered startup headquarters in industry *j* and state *s* during Q1 2010 to Q4 2015, and S_{weak} is the set of weak-enforceability states as we have defined them before. The identifying variation comes from differential treatment intensity: industries whose startups are concentrated in states with weak NCA enforcement experienced larger increase in trade secret protection following the federal DTSA. The resulting local average treatment effect is the causal effect of organization capital intensity for startups in industries with greater pre-2016 exposure to weak-NCA states, for which the DTSA most strongly increased the marginal benefit of building and protecting organization capital.

The relevance condition requires that our instrument predicts organization capital intensity. This is plausible as the DTSA increased the payoff to investing in non-patentable know-how, particularly in states where state enforcement of NCAs had been weak, and federal protection therefore added incremental bite. Empirically, the first stage of the IV regressions shows a strong correlation between our instrument and our proxies for organization capital intensity.

The exclusion restriction requires that, conditional on controls, the instrument affects startup valuations only through its effect on organization capital intensity. Aggregate post DTSA effects are absorbed by time fixed effects, so identification relies on cross-industry differences in pre-determined exposure to weak-NCA states, where the DTSA plausibly increased the marginal return to investing in and protecting organizational know-how. Cross-industry variation in pre-2016 geographic exposure to weak-NCA states thus maps the legal shock into real changes in organization-capital investment rather than purely financial revaluation. [x]

To verify that the instrument operates through the organization capital channel rather than through other features of weak-NCA-exposed industries, we re-estimate the IV regressions using a triple-interaction instrument that conditions on industries' pre-2016 reliance on organization capital-intensive roles, ${Z^{\mathrm{Org}}}_{j,t} = Org\ Cap\ Employees_{j,\,pre} \times \text{Weak-NCA Exp}_{j,\,pre} \times 1_{t \geq \text{DTSA Q2 2016}}$. The triple interaction directly conditions on the organization capital channel, since identification relies on the differential post-DTSA effect in weak-NCA states for industries that rely most on organization capital-intensive roles. The IV estimates using this measure are reported in Table IA.B.6 and are very similar to those obtained with the

[x] A related concern is that stronger trade secret protection may affect innovation activity, such as R&D investment or the choice between patenting and secrecy (e.g., Png, 2017). Our instrument mitigates this concern by conditioning on pre-determined organization capital intensity, making it less likely that identification operates through broader intangible investment channels. Moreover, the reduced-form evidence in Table 4, Panel A shows that the DTSA shock increases organization capital intensity but not knowledge capital intensity among young public firms, suggesting that the shock operates primarily through the organization capital channel for firms more comparable to our startup sample.

double interaction instrument, consistent with the instrument working through the organization capital channel.

To identify the effect of funding flows on the likelihood of becoming a large startup, we also need an instrument correlated with industry fund flows in the prior quarter but uncorrelated with the industry's potential. We instrument industry venture capital flows using a Bartik-style instrument that interacts pre-determined state-industry shares with shocks to local funding supply at the state level. For each startup, the instrument assigns the pension funding shock of the startup's headquarters state, weighted by the historical share of startups in the same industry located in that state. This approach follows a growing literature that exploits shocks to limited partner (LP) capital supply to generate exogenous variation in venture capital funding (e.g., Mollica and Zingales, 2007; Popov and Roosenboom, 2009; Samila and Sorenson, 2011; González-Uribe, 2020; Chen and Ewens, 2025). Specifically, our instrument is defined as:

$$Z^{\text{Flows}}{}_{s,j,t} = \text{Share}_{s,j}^{2010-2013} \times \text{Shock}_{s,t-1}$$

where $Share_{s,j}^{2010-2013}$ is the fraction of startups in industry j located in state s during 2010-2013, and $Shock_{s,t-1}$ is the aggregate pension fund contributions in state s in $t-1$ obtained from the Public Plans Database (PPD). The instrument varies at the firm level through the startup's headquarters state. Specifically, each startup receives the pension funding shock of its state, weighted by the pre-determined share of its industry located in that state. Intuitively, when pension fund contributions in a state increase, local venture capital fundraising ability increases, so that startups in industries that have been historically important in that state receive more funding. Importantly, this predetermined exposure structure means that even if pension contributions respond to general economic conditions that also affect startup outcomes, identification comes from the differential impact across states based on their historical industry composition. Our IV estimates show that this instrument is highly relevant for industry venture capital funding.

For the exclusion restriction to hold, the instrument should affect the likelihood that a startup becomes large only through its effect on venture capital flows. In our setting, the key assumption is that the state-industry shares used as exposures to local funding shocks are predetermined and uncorrelated with subsequent shocks to industry growth potential (Goldsmith-Pinkham, Sorkin, and Swift, 2020). While certain states may have had historical advantages in particular industries, the predetermined shares are unlikely to be systematically related to time-varying industry-specific growth opportunities that could affect startup success through channels other than venture capital availability.

We report first-stage diagnostics to assess the relevance condition. In specifications with one endogenous regressor, we compute the Kleibergen-Paap rk Wald F-statistic using standard errors clustered at the startup level. The Kleibergen-Paap statistic provides a heteroskedasticity-robust test of weak identification and is appropriate in our setting with clustered standard errors. The first-stage F-statistics comfortably exceed conventional weak instrument thresholds, indicating that the instruments have strong predictive power for organization capital intensity. In specifications where we instrument both organization capital intensity and industry funding flows, we report the Kleibergen-Paap rk Wald F-statistic for the system of endogenous regressors. The statistic indicates that the instruments jointly satisfy the rank condition and are sufficiently strong in the first stage.[y]

Panel A of Table 6 reports results from the panel regressions, estimated using 60,830 firm-quarter observations and standard errors clustered at the firm level. Column (1) presents OLS estimates. Column (1) shows that a startup is more likely to become large if it has a higher organization capital intensity using the LinkedIn-based measure. The coefficient on industry funding flows is insignificant. As expected, the indicator variable *Scale* has a positive and significant coefficient. Startups closer to San Francisco are more likely to be large. The startup's age and the private market MB are insignificant in the OLS regressions. The insignificant estimate for the private market MB is inconsistent with the argument that startups stay private because their private market valuation is excessively high.

[y] With one endogenous regressor and one instrument, the Kleibergen-Paap rk Wald F-statistic is numerically equivalent to the Montiel Olea-Pflueger (2013) effective F-statistic. We therefore report the Kleibergen-Paap rk Wald F-statistic throughout for consistency across specifications.

Column (2) presents the first-stage result of the IV regression that instruments for organization capital. We find that our instrument for organization capital intensity has a positive coefficient, significant at the 1% level. In Column (3), we use the instrument in the second stage regression. We find that instrumented organization capital intensity has a positive coefficient of 0.058 significant at the 1% level. In the IV regressions, industry funding flows, scale, and age increase the likelihood of a startup becoming large.

In Column (3), we do not instrument industry funding flows. We now turn to a second-stage regression where we instrument both organization capital intensity and industry funding flows. Column (4) shows the first stage regression for industry funding flows. We find that the coefficient of the instrument is significantly positive, as predicted. Column (5) shows the first stage for organization capital intensity based on the LinkedIn measure. We find a positive and significant coefficient on the instrument. Column (6) reports the estimates of the second-stage regression. The coefficient on the instrumented organization capital intensity is positive and significant at the 1% level, and it is similar to the coefficient in Column (3). Based on this specification, a one standard deviation increase in organization capital intensity increases the likelihood of becoming large by 1.32 percentage points, or 89% ($(0.24 \times 0.059)/0.016$) relative to its unconditional mean.[z] The coefficient on instrumented industry funding flows is not significant.

The IV estimates for the share of organization capital employees in Columns (3) and (6) are substantially larger than the corresponding OLS estimates in Column (1). This pattern is consistent with attenuation bias arising from measurement error in organization capital intensity and with the fact that the DTSA-based instrument identifies a local average treatment effect for startups whose organization capital investment responds to changes in trade-secret protection. These startups, for which stronger protection of unpatentable intangible assets materially increases the returns to organization capital, are precisely the firms for which organization capital is most important for scaling and delaying exit.

We now turn in Panel B of Table 6 to regressions using the organization capital intensity of young firms in an industry as proxy for the organization capital intensity of startups in that industry. The regressions use

[z] The standard deviation of organization capital intensity in the panel data is 0.24 and the unconditional mean of achieving large status is 0.016.

84,119 startup-quarter observations. We continue to use year-quarter fixed effects and include additional regressors that are the total q, the log of assets, cash over total assets, COGS over total assets, the percentage of loss firms for young public firms in the startup's industry, and the industry private market MB. As in Panel A, we find a positive correlation between organization capital intensity and large status in the OLS results reported in Column (1). We then turn to regressions where we instrument organization capital and both organization capital and industry funding. The results are consistent with the results of Panel A. Columns (2), (4), and (5) show first-stage regressions. With the second-stage regressions, we find a highly significant coefficient for instrumented organization capital intensity in Columns (3) and (6). The coefficient on instrumented funding flows is positive, but only significant at the 10% level.

The evidence of this section supports our conjecture that startups that rely on organization capital intensity and scale for their business model are more likely to become large rather than exit earlier through a trade sale or an IPO. There is only modest evidence that exogeneous increases in funding flows increase the probability of a startup becoming large.

6. Organization capital and exit

We hypothesize that startups with an organization-capital-intensive business model seeking to benefit from scale and network effects benefit from staying private longer. In this section, we use Cox proportional hazard regressions to estimate how organization capital is related to the hazard of exit through an acquisition or a listing.

In Columns (1) and (2) of Table 7, we estimate Cox proportional hazard regressions for the time to exit. Column (1) uses all VC startups and Column (2) restricts the sample to large startups, allowing us to examine whether organization capital intensity explains exit timing conditional on being large. Panel A uses the organization capital intensity measure based on the LinkedIn data, and Panel B uses organization capital intensity measured from young public firms in the startup's industry. We use the same firm- and industry-level controls as in Panels A and B of Table 6, respectively, but do not include fixed effects.[aa] In addition, we include macroeconomic variables, as it is known that such variables affect exit timing. The coefficients in Columns (1), (2), (5), and (6) have the interpretation of hazard ratios, so that a coefficient above one means that exit is faster and one below one means that exit is expected farther in the future.

In Panel A, we find that startups with more organization capital exit more slowly, both in the full sample and among large startups. Based on Column (1), a one standard deviation increase in organization capital intensity is associated with a 19% lower hazard rate of exit in any given quarter. We find consistent results in Panel B when we use industry organization capital intensity. We also find that the hazard of exit differs depending on the level of the macroeconomic variables. Exit is more likely if the IPO volume is high, if first-day IPO returns are low, if the market has performed well, if market valuations are low, if credit spreads are high, and if interest rates are low.

Organization capital intensity may be endogenous in the exit regressions because unobserved firm characteristics such as managerial ability or entrepreneurial talent could affect both the accumulation of organization capital and the likelihood of exit. We therefore estimate regressions using instrumented organization capital intensity via a control function approach. Specifically, in Columns (3) and (4), we report the first-stage regressions, where we regress organization capital on the instrument defined in Section 5. To evaluate the strength of the instrument in the control function specifications, we report the first-stage F-statistics corresponding to the regression used to construct the residuals. In Columns (3) and (4), the first-stage F-statistics remain significantly above conventional weak-instrument thresholds. The second-stage results are in Columns (5) and (6). In both panels and samples, we find that startups with greater organization capital intensity have a lower hazard of exit. The coefficient on the first stage residual is larger than one and strongly significant. Hence, the unobserved characteristics that lead firms to invest more in organization capital beyond what is predicted by observables and the instrument are positively correlated

[aa] We exclude startup age from the Cox regressions in Panel A because the Cox model accounts for duration through the baseline hazard function and age and duration are mechanically related. We continue to include the average age of young public firms in the startup's industry as a control in Panel B.

with the exit hazard. This implies that the OLS estimates in Columns (1) and (2) are biased toward one and thus understate the true effect of organization capital on delaying exit. Consistent with this, the instrumented hazard ratios in Columns (5) and (6) are smaller than the OLS ones, suggesting that the economic effect of organization capital on exit timing is larger than what the OLS captures. While scale has a coefficient in Columns (1) and (2) insignificantly different from one, the coefficient on scale in Column (5) of Panel A is surprisingly significantly greater than one. In Panel B, where we control for additional accounting characteristics, the coefficient on scale is smaller than one so that startups relying on scaling delay exit. The results of this section suggest that organization capital intensity affects the duration of large private status. These results are consistent with a business model in which organization capital of young firms is most efficiently accumulated by remaining private longer.

7. Large startups at the IPO

With our LinkedIn data, we can plot the evolution of organization capital intensity for startups around the IPO. We do so in Figure 6. We see that large startups experience a decrease in organization capital intensity in the three years before the IPO but then their organization capital intensity is stable after the IPO. The plot for the other startups is more volatile before the IPO. The organization capital intensity for small startups is always at least 10 percentage points lower than the organization capital intensity for large startups. Organization capital intensity for small startups increases in the year before the IPO but then falls after the IPO and is stable. Figure 6 shows that large startups have higher organization capital compared to small startups and that their organization capital intensity is lower after the IPO.[bb]

We now use a sample of large startups at the IPO to provide additional evidence supporting our explanation. With our explanation, we would expect large startups to invest more in organization capital before the IPO than other startups. Further, with the founder hypothesis, we would expect the effect to be

[bb] If we estimate a DiD regression for large startups where treatment is the IPO, the dependent variable is organization capital intensity, and the regressors are firm and year-quarter fixed effects and the treatment indicator, the coefficient on the treatment indicator is -0.009 and is significant at the 5% level.

weaker for large startups going public with more founder power. Firms that go public through an IPO must disclose accounting data for the two years preceding the offering. The advantage of using data from IPOs of large startups is that we have company-specific accounting data from the IPO prospectus. A limitation of the IPO prospectus data is that we have only one observation, so that we cannot estimate the stock of organization capital. We assume that the stock is proportional to the investment in organization capital for the year before the IPO. A caveat for our investigation in this section is that startups choose to exit and those that do exit may differ from those that do not.

In Panel A of Table 8, we compare large startup IPOs to matching startup IPOs to test our hypotheses. With our database, we can match each large startup that goes public with a small startup that goes public and raised funds in the same year, at a similar valuation, with similar cumulative funding, and of similar age as the then future large startup in its last pre-large startup round. The logic of the match is that the matching firms have the same funding history up to and including the pre-large startup round for the large startup. Since our explanation has large startups staying private because this allows them better performance, it would be contrary to our explanation to find weak performance of the large startups that IPO compared to other startups. We find that the evidence is supportive of our explanation. First, we find that the large startups have a higher first-day return and higher three-month return than the matching startups. Both the first day and the three-month returns are positive. Second, we see that large startups have more assets, greater gross profits, and lower frequency of negative income. We find that large startups have a lower cash and short-term instruments to assets ratio, but their ratio is nevertheless extremely high (59%) so that immediate need for cash may not be the reason for the IPO. With our explanation, we would expect a higher SG&A to assets ratio, as a proxy for organization capital. We find that this is the case. In contrast, we find that the matching startups have an R&D to total assets ratio that is more than two times larger than the R&D to total assets ratio of the large startups. We also report our measure of organization capital that uses LinkedIn data. We find that large startups are more organization-capital-intensive than other startups. The average share of organization capital employees is 0.37 for large startups and 0.22 for the other startups.

The difference is significant at the 1% level. Tangible assets and capital expenditures are small for both the large startups and their matches.

The last row of Panel A of Table 8 shows that large startups are much more likely to have dual-class share structures than their matches. In general, dual-class share structures arise endogenously in circumstances where the founder is powerful (Aggarwal et al., 2022). If, under such circumstances, agency costs arising from founder power are important, we would expect large startups with dual shares to perform worse than other large startups. We therefore compare the performance of large startup IPOs with a dual-class share structure to the performance of other large startups in Table 8, Panel B. We also compare the organization capital intensity of dual-class share IPOs to other IPOs to assess whether organization capital plays less of a role when the founder is more powerful. We are not claiming causality for these comparisons but nevertheless view them as instructive.

We find no evidence of poorer performance of dual-class IPOs compared to other large startup IPOs. Dual-class IPOs have more assets and gross profits, but less cash. The frequency of negative income is the same for both types of IPOs. Strikingly, the dual-class IPOs invest more in organization capital and less in R&D. The difference for organization capital is large. For instance, median SG&A to assets is 43% for dual-class IPOs and 15% for the other IPOs. Using our LinkedIn measure of organization capital intensity, we find that the average organization capital intensity for large startups with dual-class shares, 0.49, is significantly larger than the average organization capital intensity for large startups without dual-class shares (0.31). This evidence seems more supportive of the view that founder control is valuable for building organization capital than the view that founder control is associated with important agency costs. Our findings seem consistent with recent evidence suggesting that dual-class share structures may be value-creating for firms at the IPO by making it more likely that the founders can carry out their business strategy (Aggarwal et al., 2022; Field and Lowry, 2022; Kim and Michaely, 2019).

In Panel C, we address a potential concern with the matching method used in Panel A of Table 8. With the matching in Panel A, we go backwards to match startups before the large startup round, knowing that this round will take place for one leg of the matched pair. This raises the concern that we match a startup that will be successful staying private to another startup that does not experience the same valuation increase. In Panel C of Table 8, we use as matches for the large startups that IPO young public firms that were not large startups at the IPO but that have reached the same valuation as the IPO valuation of the large startups. In other words, we compare large startup IPOs to small startup IPOs that have done well after the IPO. We see that the large startups are smaller and have lower sales and have more cash and short-term investments. The large startups have the same average gross profits, but lower gross profits at the median. The frequency of negative income is much higher for large startups than for their matches. While large startups have less tangible capital, they invest more in SG&A and in R&D. Lastly, the large startups have a higher percentage of dual share stock. The evidence in Table 8, Panel C, supports the evidence in Panel A of the table that startups that go public earlier have a business model that relies less on organization capital.

To examine whether the differences documented in Table 8, Panels A and C, remain after controlling for observable firm characteristics, we estimate regressions relating large-startup status to pre-IPO accounting variables and controlling for industry effects and macroeconomic conditions. The results, reported in Table IA.B.7 in the Internet Appendix, confirm the patterns of Table 8. Most importantly, large startups have much higher SG&A / total assets than comparable firms, even after controlling for size, cash holdings, and fixed effects. The effects for R&D / total assets are much weaker. The regressions therefore reinforce the distinction between organization capital and knowledge capital and show that the differences shown in Table 8 are not attributable to simple differences in size, scale or industry composition.

Overall, the evidence presented in this section provides additional support for our conjecture that the importance of organization capital distinguishes large startups from other startups and explains why these startups stay private.

8. Conclusion

Over the past two decades, many startups have reached large valuations without accessing public markets, a pattern that cannot be explained by private market funding availability alone. We argue and show that this pattern is consistent with a value-maximization framework in which startups whose business models rely heavily on organization capital choose to stay private while building the organizational assets necessary to achieve scale and network effects through the use of digital technologies.

Organization capital is firm-specific, difficult to observe and monitor, largely expensed in financial statements, and often close to worthless unless scale is achieved. Premature exit, whether through a public listing or a trade sale, can expose fragile organization capital to disclosure, imitation, employee mobility, or disruptive integration before it is sufficiently developed. Using a novel LinkedIn-based measure of organization capital intensity for startups, we show that organization-capital-intensive startups are significantly more likely to attain large private status and to exit later.

To establish causality, we exploit the introduction of the Defend Trade Secrets Act (DTSA) of 2016 in combination with pre-existing cross-state differences in non-compete agreement (NCA) enforceability. The DTSA increased the marginal protection of unpatentable intangible assets, especially in states where NCA enforcement had previously been weak. We show that this interaction increases organization capital investment among both young public firms and startups. We then construct an instrument that combines industry-level reliance on organization-capital-intensive roles, geographic exposure to weak-NCA states, and the post-DTSA period. The resulting instrumental-variable estimates confirm a direct causal effect of organization capital intensity on the probability of becoming a large startup.

We find no evidence that higher private-market valuations increase the likelihood of reaching large status, which is inconsistent with overvaluation-based explanations. We also find limited support for founder agency as the primary driver of delayed exit.

Overall, our results are consistent with a value-maximization framework in which organization-capital-intensive startups remain private because private status provides operational and financing advantages while organization capital is being built. Once organization capital is sufficiently developed to harvest scale and network effects, the relative benefits of remaining private decline. Our framework highlights the importance of organization capital in firm decisions. It helps understand why large startups have become more common and why the likelihood that a startup becomes a large startup differs so much across industries.

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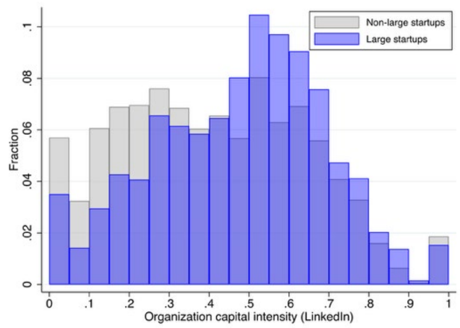
Figure 1. Distribution of organization capital intensity

This figure compares the distribution of organization capital intensity using the LinkedIn data between large startups and non-large startups. Panel A shows the histograms, and Panel B the empirical cumulative distribution functions.

Panel A: Histogram



Panel B: Cumulative distribution function

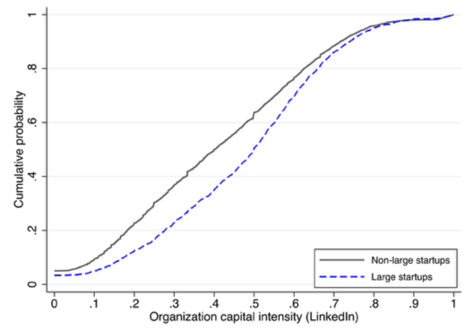
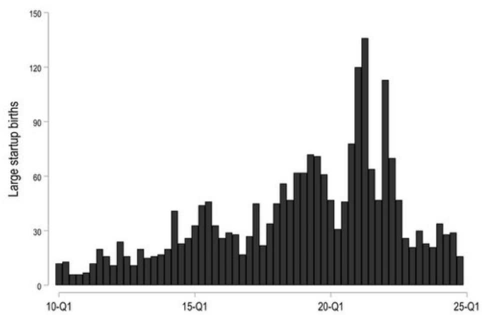


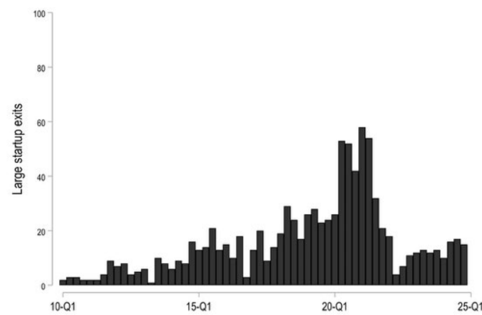
Figure 2. Births, exits, and total number for U.S. large startups

This figure shows the number of new U.S. large startups by quarter (Panel A), the number of large startup exits by quarter (Panel B), and the cumulative number of U.S. large startups born, exited, and in existence by quarter (Panel C). The sample consists of 2,222 U.S. large startups, defined as private companies with a post-money headline valuation of at least $300 million. The sample period is from Q1 2010 to Q4 2024.

Panel A: Large births



Panel B: Large exits



Panel C: Large startups in existence

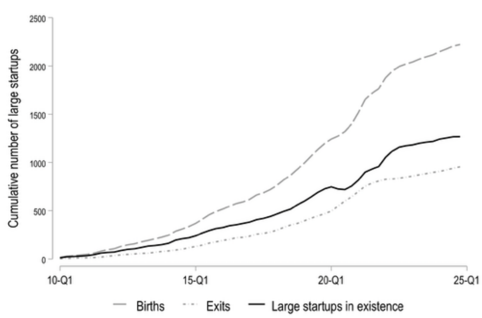


Figure 3. Sectoral distribution of organization, knowledge, and tangible capital intensities

This figure shows the average organization, knowledge, and tangible capital intensities for each CB Insights sector in the 2010s using data from public firms. Organization and knowledge capital are capitalized SG&A expenses and R&D expenses, which we calculate adapting the approach of Ewens, Peters, and Wang (2024). Tangible capital is gross property, plant, and equipment (PP&E).

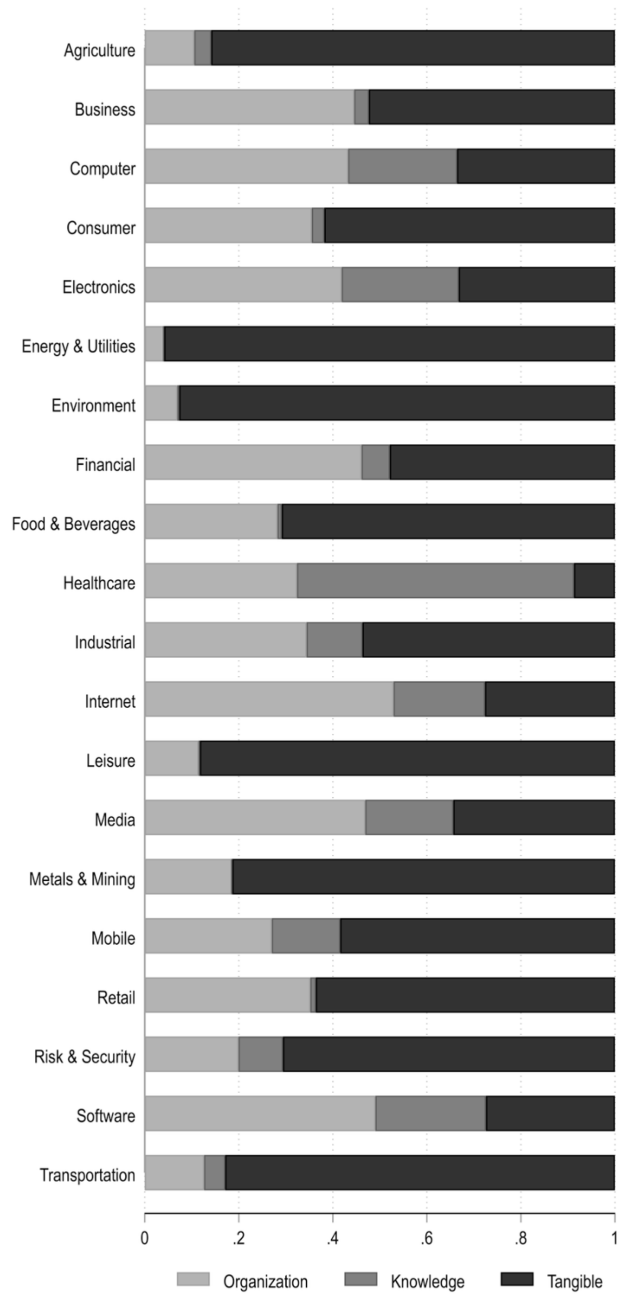


Figure 4. U.S. States with weak enforcement of NCAs

This map highlights U.S. states classified as having weak enforcement of non-compete agreements pre 2016 based on the Golubov and Zhong (2024) state-level NCA enforceability score. We classify the state with a below-median score to be weak enforceability states.

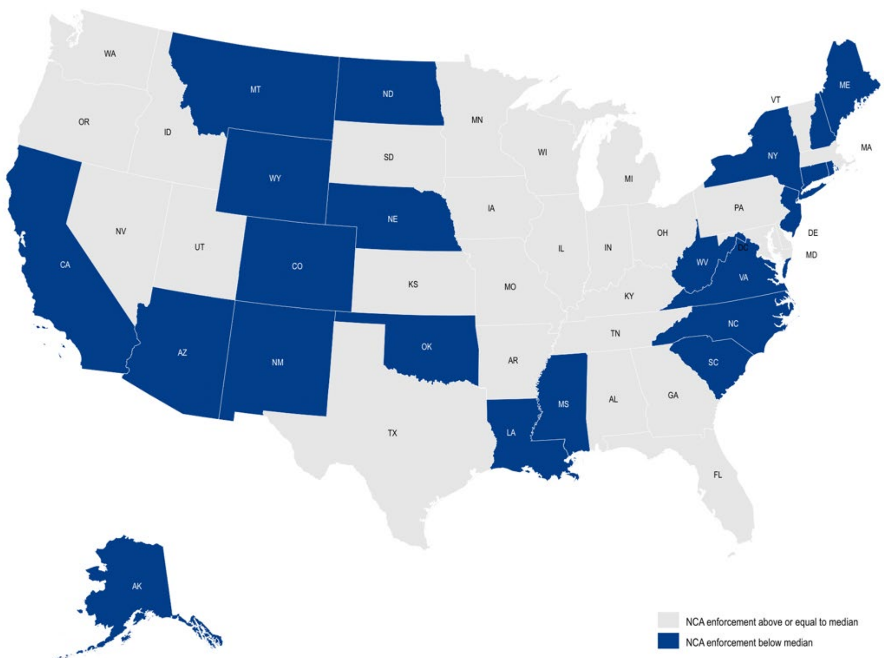
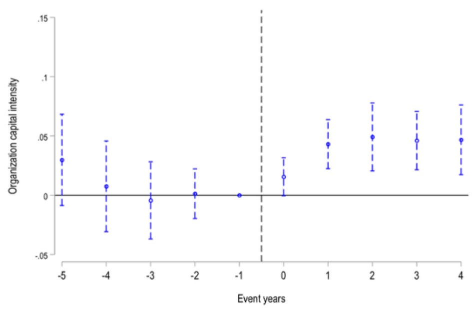


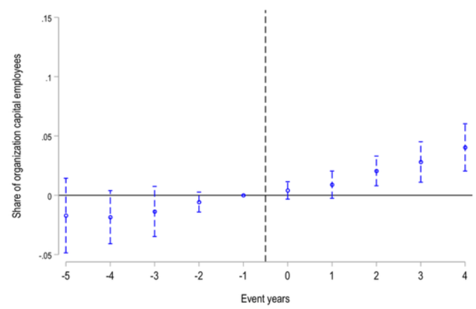
Figure 5. Dynamic treatment effects around the enactment of the Defend Trade Secrets Act of 2016

The figure plots the β coefficient estimates and 95% confidence intervals from the following regression: $Y_{ijst} = \sum_{t=-5}^{5} \gamma_t Event\,year_t + \sum_{t=-5}^{5} \beta_t Ex\,ante\,NCA_s \times Event\,year_t + \mu_j + \delta_s + \gamma_t + \epsilon_{ijst}$, where i indexes firms, j industries, *s* states, and *t* years. In Panel A, Y_{it} is organization capital intensity. In Panel B, Y_{it} is the fraction of startups' organization capital employees. In Panel C, Y_{it} is *Large status*, which equals one from the quarter a firm reached a post-money headline valuation of at least $300 million until the end of the sample and zero otherwise. Treatment is defined by *Ex ante weak-NCA*, which equals one if the startup's state has an NCA enforceability score, obtained from Golubov and Zhong (2024), below the sample median before the enactment of the DTSA. *Post DTSA* equals one for quarters Q2 2016 and after. In Panels B and C, we use propensity scores to match each treated startup to the nearest neighbor control startup in states with an NCA enforceability score above the median based on cumulative funds raised, age, and headline post-money valuation in Q4 2015. $Event\ year_t$ is a vector of year indicator variables where zero corresponds to Q2 2016. In Panel A, μ_j, $\delta_s, and\ \gamma_t$ denote industry, state, and year-quarter fixed effects, respectively. In Panels B and C, we replace the industry fixed effects with firm fixed effects and exclude the state fixed effects. Standard errors are clustered at the firm and state levels. The dashed vertical line represents the mid-point between the pre- and post-treatment period.

Panel A: Organization capital intensity



Panel B: Organization capital employees



Panel C: Large status

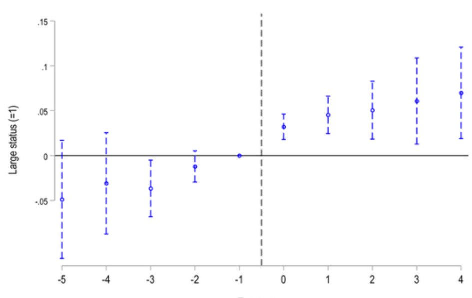


Figure 6. Evolution of the share of organization capital employees

This figure shows the average share of organization capital employees of large and other startups in a three-year window around IPO. Large startups are private companies with a post-money headline valuation of at least $300 million. Organization capital employees are employees in selected managerial, technical and engineering roles, and creative positions. The appendix contains detailed variable definitions.

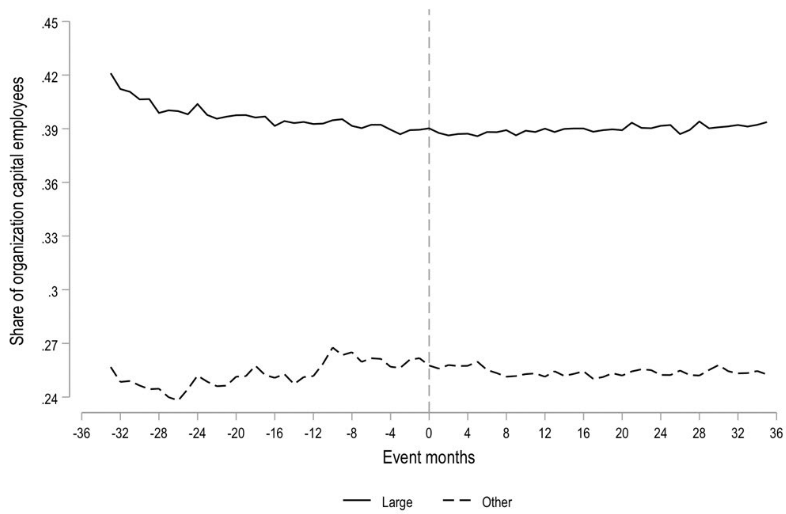


Table 1. Summary statistics

Panel A of this table shows summary statistics on the financing, post-money headline valuations, and exit of 7,234 U.S. startups, of which we classify 2,222 as large and the remaining ones as small. Large startups are defined as private companies that reach a post-money headline valuation of at least $300 million. Columns (4) to (7) report statistics separately for large and small startups. Panel B shows additional summary statistics for large startups only. The sample period is Q1 2010 to Q4 2024. The stars correspond to *t*-tests (Wilcoxon tests) of differences in means (medians). Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. The appendix contains detailed variable definitions.

Panel A: Large and non-large startups

	All startups			Large startups		Small startups		Differences (Large-Small)	
	Obs	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Organization capital intensity (LinkedIn)	6,516	0.42	0.41	0.46	0.45	0.40	0.38	0.06^{***}	0.07^{***}
Industry organization capital intensity	7,234	0.43	0.48	0.45	0.51	0.42	0.45	0.03^{***}	0.06^{***}
Number of equity rounds	7,234	4.64	4.00	6.43	5.00	3.84	4.00	2.59^{***}	1.00^{***}
Total equity funding ($ millions)	7,234	197.82	89.50	422.12	212.00	98.38	69.86	323.73^{***}	142.14^{***}
Private market MB	6,929	2.78	1.81	4.53	3.27	1.95	1.37	2.58^{***}	1.90^{***}
PMV after last private round ($ billions)	6,131	0.69	0.18	2.34	0.88	0.19	0.13	2.15^{***}	0.75^{***}
Equity fraction, funds raised	7,234	0.85	1.00	0.88	1.00	0.83	1.00	0.05^{***}	0.00
Exit (=1)	7,234	0.37	0.00	0.43	0.00	0.34	0.00	0.09^{***}	0.00
IPO (=1)	2,656	0.26	0.00	0.37	0.00	0.19	0.00	0.18^{***}	0.00
SPAC (=1)	2,656	0.05	0.00	0.06	0.00	0.05	0.00	0.02^{**}	0.00
Direct listing (=1)	2,656	0.00	0.00	0.01	0.00	0.00	0.00	0.01^{***}	0.00
M&A (=1)	2,656	0.53	1.00	0.35	0.00	0.63	1.00	-0.28^{***}	-1.00^{***}
Down round (=1)	2,656	0.04	0.00	0.11	0.00	0.01	0.00	0.10^{***}	0.00
Failed (=1)	2,656	0.11	0.00	0.09	0.00	0.13	0.00	-0.04^{***}	0.00
Age at exit (years)	2,656	7.93	7.20	8.55	7.89	7.58	7.00	0.97^{***}	0.89^{***}
Scale (=1)	7,234	0.42	0.00	0.49	0.00	0.39	0.00	0.09^{***}	0.00
Near San Francisco (=1)	7,234	0.32	0.00	0.40	0.00	0.29	0.00	0.12^{***}	0.00

Panel B: Large startups only

	Obs	Mean	Median
Years btw. founding and large status	2,222	5.91	5.11
Equity rounds btw. founding and large status	2,222	3.01	3.00
PMV large round ($ billions)	2,222	0.84	0.50
Total funding until large status ($ millions)	2,222	153.33	112.00
Total funding after large status ($ millions)	2,222	370.02	108.00
Years between exit and large status	955	2.50	1.99

Table 2. Summary statistics for large startups with an exit during the sample period

The table shows summary statistics for the 955 large startups that had an exit. Startups exit the sample because of a down round, a failure (outright failure or acquisition at less than 25% of the large startup post-money headline valuation), a public listing through an IPO, a de-SPAC transaction, a direct listing, or an acquisition. The sample period is Q1 2010 to Q4 2024.

	Down (105 obs.)		Failed (87 obs.)		IPO (356 obs.)		SPAC (62 obs.)		Direct listings (9 obs.)		M&A (336 obs.)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Years between large status and exit	3.92	3.62	3.29	2.82	2.22	1.51	3.68	2.90	6.01	6.24	1.84	1.16
Equity rounds between large status and exit	2.89	2.00	2.33	1.00	2.37	1.00	3.79	2.00	6.44	4.00	0.92	0.00
PMV large round ($ billions)	0.61	0.42	1.03	0.50	0.79	0.48	1.02	0.53	0.61	0.50	0.67	0.44
PMV at exit			0.48	0.32	3.63	0.86	3.50	2.40	17.57	6.08	1.39	0.51
Total funding while private ($ millions)	686.26	231.47	497.10	271.80	725.63	370.94	686.79	442.67	789.02	538.67	362.29	168.86
PMV at exit/PMV large round			0.91	0.89	5.53	1.31	5.87	3.85	33.25	12.75	2.04	1.00
Exit MB			2.57	1.53	6.98	4.14	7.25	5.36	27.29	15.37	6.98	3.86
Private market MB			2.79	2.12	4.36	2.23	4.96	3.06	16.41	15.37	4.40	3.27
PMV at exit $<$ total fundraising (=1)			0.25	0.00	0.10	0.00	0.03	0.00	0.00	0.00	0.03	0.00

Table 3. Industry sector comparisons of large startups, all VC-backed startups, public firms, and IPOs

The table reports firm counts by CB Insights industry sectors. Columns (1) and (2) show the number and % of large startups, Columns (3) and (4) show the number and % of VC-backed startups that obtained at least $50m in cumulative financing between Q1 2010 and Q4 2024, Columns (5) and (6) show the total number and % of public firms, and Columns (7) and (8) show the number and (%) of IPOs. The appendix contains detailed variable definitions.

	Large startups		All startups		Public firms		IPOs	
	N	%	N	%	N	%	N	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agriculture	6	0.3	45	0.6	18	0.2	7	0.2
Business	434	19.5	1,073	14.8	459	5.6	583	16.3
Computer	89	4.0	247	3.4	907	11.0	487	13.6
Consumer	42	1.9	139	1.9	179	2.2	80	2.2
Electronics	35	1.6	160	2.2	1,000	12.2	511	14.3
Energy & Utilities	63	2.8	269	3.7	312	3.8	72	2.0
Environment	16	0.7	65	0.9	42	0.5	6	0.2
Financial	260	11.7	794	11.0	1,247	15.2	337	9.4
Food & Beverages	20	0.9	79	1.1	221	2.7	60	1.7
Healthcare	414	18.6	2,047	28.3	1,136	13.8	604	16.8
Industrial	116	5.2	380	5.3	812	9.9	181	5.0
Internet	364	16.4	913	12.6	145	1.8	25	0.7
Leisure	39	1.8	101	1.4	185	2.3	61	1.7
Media	50	2.3	131	1.8	280	3.4	79	2.2
Metals & Mining	2	0.1	10	0.1	66	0.8	15	0.4
Mobile	68	3.1	221	3.1	192	2.3	33	0.9
Retail	1	0.0	15	0.2	254	3.1	96	2.7
Risk & Security	133	6.0	336	4.6	11	0.1	7	0.2
Software	51	2.3	142	2.0	476	5.8	237	6.6
Transportation	19	0.9	67	0.9	278	3.4	104	2.9
Total	2,222	100	7,234	100	8,220	100	3,585	100

Table 4. Changes in capital intensities and large status around the enactment of the Defend Trade Secrets Act of 2016

The table reports results from difference-in-differences regressions around the enactment of the Defend Trade Secrets Act (DTSA) of 2016. In Panel A, the dependent variables are organization capital intensity, knowledge capital intensity, and tangible capital intensity. Organization capital intensity is the ratio of capitalized SG&A expenses to the sum of capitalized SG&A expenses, capitalized R&D expenses, and tangible capital, which we calculate adapting the approach from Ewens, Peters, and Wang (2024) for the capitalization of SG&A and R&D expenses. Knowledge and tangible capital intensity are defined in a similar way, replacing organization capital in the numerator with either knowledge or tangible capital. In Panel B, the dependent variable is startup-level organization capital intensity based on the LinkedIn data. *Ex ante Ln(Cumulative funding)*, *Ex ante Ln(Age)*, and *Ex ante Ln(Headline valuation)* are the log of cumulative funds raised, age, and post-money headline valuation in Q4 2015. In Panel C, the dependent variable is *Large status (=1)*, which equals one from the quarter a firm reached a post-money headline valuation of at least $300 million until the end of the sample and zero otherwise. In Panels B and C, we use propensity scores to match each treated startup to the nearest neighbor control startup in states with an NCA enforceability score above the median based on cumulative funds raised, age, and headline post-money valuation in Q4 2015. *Ex ante Ln(Cumulative funding)*, *Ex ante Ln(Age)*, and *Ex ante Ln(Headline valuation)* are the log of cumulative funds raised, age, and post-money headline valuation in Q4 2015. Organization capital employees decile is the decile of the fraction of organization capital employees in Q4 2015. Treatment is defined in all Panels by Ex ante weak-NCA, which equals one if the startup's state has an NCA enforceability score, obtained from Golubov and Zhong (2024), below the sample median before the enactment of the DTSA. Post DTSA equals one for quarters Q2 2016 and after. We estimate the regressions with a symmetric five-year window around Q2 2016. P-values based on standard errors clustered at the firm and state levels are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. The appendix contains detailed variable definitions.

Panel A: Capital intensities based on young public firms			
	Organization capital intensity	Knowledge capital intensity	Tangible capital intensity
	(1)	(2)	(3)
Ex ante weak NCA× Post DTSA	0.034***	−0.004	−0.030*
	(0.003)	(0.760)	(0.052)
Fixed effects			
Industry	✓	✓	✓
State	✓	✓	✓
Year-quarter	✓	✓	✓
Observations	26,628	26,628	26,628
Adjusted R^2	0.24	0.66	0.49

Panel B: Organization capital intensity (LinkedIn)

	Organization capital intensity (LinkedIn)				
	(1)	(2)	(3)	(4)	(5)
Ex ante weak NCA× Post DTSA	0.030***	0.029***	0.031***	0.029***	0.029***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex ante Ln(Cumulative funding) × Post DTSA		0.001			0.002
		(0.477)			(0.567)
Ex ante Ln(Age) × Post DTSA			−0.035***		−0.045***
			(0.000)		(0.000)
Ex ante Ln(Headline valuation) × Post DTSA				0.006**	0.011**
				(0.012)	(0.041)
Fixed effects					
Firm	✓	✓	✓	✓	✓
Year-quarter	✓	✓	✓	✓	✓
Observations	82,146	82,146	82,146	82,146	82,146
Adjusted R^2	0.75	0.75	0.76	0.75	0.76

Panel C: Startups' large status

	Large status (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ex ante weak NCA× Post DTSA	0.066***	0.060***	0.066***	0.053***	−0.030	−0.022
	(0.001)	(0.001)	(0.001)	(0.006)	(0.342)	(0.453)
Ex ante weak NCA × Org. capital decile × Post DTSA					0.016***	0.012***
					(0.005)	(0.005)
Ex ante Ln(Cumulative funding) × Post DTSA		0.059***				0.029***
		(0.000)				(0.000)
Ex ante Ln(Age) × Post DTSA			0.002			−0.070***
			(0.929)			(0.000)
Ex ante Ln(Headline valuation) × Post DTSA				0.078***		0.067***
				(0.000)		(0.000)
Fixed effects						
Firm	✓	✓	✓	✓	✓	✓
Year-quarter	✓	✓	✓	✓	✓	✓
Org. capital decile × Quarter					✓	✓
Observations	82,146	82,146	82,146	82,146	82,146	82,146
Adjusted R^2	0.61	0.62	0.61	0.63	0.62	0.64

Table 5. Pre-treatment balance between treated and control startups

The table reports differences in means of pre-treatment characteristics for treated and control startups in Q4 2015, the last quarter before the enactment of the DTSA. Treatment is defined by *Ex ante weak-NCA*, which equals one if the startup's state has an NCA enforceability score, obtained from Golubov and Zhong (2024), below the sample median before the enactment of the DTSA. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. The appendix contains detailed variable definitions.

	Control	Treated	Difference
Post-money valuation ($ millions)	0.239	0.364	-0.125^{**}
Cumulative funding ($ millions)	57.164	70.327	-13.163^{**}
Age (years)	4.585	4.775	-0.190^{***}
Private market-to-book	0.051	0.036	0.016
Observations	1,203	1,876	

Table 6. Panel regressions of the likelihood of becoming a large startup

The table reports results from panel regressions of the determinants of the likelihood of becoming a large startup. The sample is a firm-quarter panel of 7,234 startups (60,830 firm-quarter observations in Panel A and 84,119 observations in Panel B) from the CB Insights database that cumulatively obtained at least \$50m in VC financing between Q1 2010 and Q4 2024. The dependent variable is *Large*, an indicator variable that equals one in the quarter a firm reached a post-money headline valuation of at least \$300 million and zero otherwise. Startups are dropped from the sample after becoming large. In Panel A, Column (1) shows OLS results, and Columns (2) to (6) present the first- and second-stages of instrumental variable regressions, where we instrument *Organization capital intensity (LinkedIn)* and *Ln(Industry funding flow)* with Z_{jt}^{Org} and Z_{sjt}^{Flows}, respectively. Z_{jt}^{Org} is the interaction between the share of industry j's pre-2016 startups located in states with weak-NCA enforceability scores and an indicator for the post-Q2 2016 period following the Defend Trade Secrets Act (DTSA). Z_{sjt}^{Flows} is the interaction between the fraction of firms in industry *j* located in state *s* during 2010-2013, and aggregate pension fund contributions in state *s* in *t-1*. In Panel B, accounting variables are calculated as the average of all young public firms in an industry. Young firms are firms in the lowest quartile of firm age each year. Panel B replaces *Organization capital intensity (LinkedIn)* with *Organization capital intensity* at the industry level. *P*-values based on standard errors clustered at the firm level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. The appendix contains detailed variable definitions.

Panel A: Organization capital intensity (LinkedIn)

	OLS	First-stage	2SLS	First-stage		2SLS
	Large (=1)	Org. capital	Large (=1)	Industry flow	Org. capital	Large (=1)
	(1)	(2)	(3)	(4)	(5)	(6)
Z_{sjt}^{Org}		0.698***		−1.378***	0.687***	
		(0.000)		(0.000)	(0.000)	
Z_{sjt}^{Flows}				0.158***	−0.004***	
				(0.000)	(0.003)	
Org. capital intensity (LinkedIn)$_{t-1}$	0.011***		0.058***			0.059***
	(0.000)		(0.000)			(0.000)
Ln(Industry funding flow)$_{t-1}$	0.000	−0.001	0.001**			0.001
	(0.643)	(0.835)	(0.037)			(0.268)
Private MB$_{t-1}$	−0.000	−0.008**	0.000	−0.030	−0.008*	0.000
	(0.819)	(0.047)	(0.644)	(0.226)	(0.064)	(0.634)
Scale (=1)	0.007***	0.062***	0.003**	0.144***	0.064***	0.003**
	(0.000)	(0.000)	(0.027)	(0.000)	(0.000)	(0.048)
Near San Francisco (=1)	0.005***	0.071***	0.001	−0.572***	0.082***	0.001
	(0.000)	(0.000)	(0.442)	(0.000)	(0.000)	(0.469)
Ln(Age)$_{t-1}$	0.001	−0.037***	0.003***	−0.040*	−0.037***	0.003***
	(0.116)	(0.000)	(0.001)	(0.067)	(0.000)	(0.001)
Year-quarter FE	✓	✓	✓	✓	✓	✓
Observations	60,830	60,830	60,830	60,830	60,830	60,830
Adjusted R^2	0.01	0.18		0.47	0.18	
KP Wald F-stat		469.38		150.65		

Panel B: Industry organization capital intensity						
	OLS	First-stage	2SLS	First-stage		2SLS
	Large (=1)	Org. capital	Large (=1)	Industry flow	Org. capital	Large (=1)
	(1)	(2)	(3)	(4)	(5)	(6)
Z^{Org}_{sjt}		0.408***		−0.326*	0.405***	
		(0.000)		(0.075)	(0.000)	
Z^{Flows}_{sjt}				0.127***	0.001***	
				(0.000)	(0.002)	
Org. capital intensity$_{t-1}$	0.015***		0.064***			0.064***
	(0.001)		(0.000)			(0.000)
Ln(Industry funding flow)$_{t-1}$	0.001**	0.019***	0.000			0.002*
	(0.049)	(0.000)	(0.933)			(0.055)
Total q$_{t-1}$	0.001	0.034***	−0.002**	0.002	0.033***	−0.001*
	(0.193)	(0.000)	(0.041)	(0.832)	(0.000)	(0.057)
Ln(Assets)$_{t-1}$	0.002**	0.007***	0.001	0.296***	0.012***	0.000
	(0.019)	(0.010)	(0.386)	(0.000)	(0.000)	(0.810)
Cash/total assets$_{t-1}$	−0.009	0.096***	−0.009	4.716***	0.201***	−0.024**
	(0.226)	(0.000)	(0.214)	(0.000)	(0.000)	(0.025)
COGS/total assets$_{t-1}$	0.004	0.933***	−0.056***	0.798***	0.960***	−0.061***
	(0.713)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Loss firm$_{t-1}$	0.002	−0.052***	0.000	−1.148***	−0.078***	0.004
	(0.653)	(0.000)	(0.986)	(0.000)	(0.000)	(0.389)
Ln(Age)$_{t-1}$	−0.001	0.198***	−0.013**	−0.154*	0.193***	−0.012**
	(0.846)	(0.000)	(0.020)	(0.078)	(0.000)	(0.028)
Industry Private MB$_{t-1}$	0.001	0.082***	0.001	−1.163***	0.061***	0.004
	(0.860)	(0.000)	(0.803)	(0.000)	(0.002)	(0.404)
Scale (=1)	0.006***	0.009***	0.005***	0.165***	0.012***	0.004***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Near San Francisco (=1)	0.006***	0.010***	0.005***	−0.427***	0.007**	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.031)	(0.000)
Year-quarter FE	✓	✓	✓	✓	✓	✓
Observations	84,119	84,119	84,119	84,119	84,119	84,119
Adjusted R^2	0.01	0.61		0.56	0.59	
KP Wald F-stat		1178.49		549.40		

Table 7. Startup exit hazard

The table reports results from Cox proportional hazard regressions of startup exit. The sample is a firm-quarter panel of 7,234 startups (115,230 firm-quarter observations) from the CB Insights database that cumulatively obtained at least \$50m in VC financing between Q1 2010 and Q4 2024. The dependent variable is the number of quarters until a firm exits the sample. We report results for all startups and large startups separately. *Large status* is an indicator variable that equals one from the quarter a firm reached a post-money headline valuation of at least \$300 million until the end of the sample and zero otherwise. Accounting variables are calculated as the average of all young public firms in the startup's industry. Young firms are firms in the lowest quartile of firm age each year. In Panel A, Columns (1) and (2) show Cox proportional hazard results, and Columns (3) to (6) present first- and second-stage instrumental variables regressions using a control function approach, where we instrument *Organization capital intensity (LinkedIn)* with Z_{jt}^{Org}. Z_{jt}^{Org} is the interaction between the industry's pre-2016 geographic footprint across weak-NCA enforcement states and an indicator for the post-Q2 2016 period following the Defend Trade Secrets Act (DTSA). Panel B replaces *Organization capital intensity (LinkedIn)* with *Organization capital intensity* at the industry level. *P*-values based on bootstrapped standard errors are shown below coefficient estimates. In each panel, Columns (1) and (2), and (5) and (6) show exponentiated log-odds ratios. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. The appendix contains detailed variable definitions.

Panel A: Organization capital intensity (LinkedIn)

	Quarters to exit		Org. capital		Quarters to exit	
	Cox		First stage		2S control function Cox	
	All	Large	All	Large	All	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Z_{jt}^{Org}			0.151***	0.100***		
			(0.000)	(0.000)		
Organization capital intensity (LinkedIn)$_{t-1}$	0.413***	0.192***			0.109***	0.046***
	(0.000)	(0.000)			(0.000)	(0.000)
Organization capital intensity (LinkedIn) residual					4.103***	4.407**
					(0.000)	(0.025)
Private MB$_{t-1}$	0.096**	0.002**	0.000	−0.005*	0.095**	0.001*
	(0.048)	(0.031)	(0.913)	(0.080)	(0.033)	(0.054)
Scale (=1)	1.106	1.055	0.082***	0.054***	1.237***	1.141
	(0.117)	(0.592)	(0.000)	(0.000)	(0.000)	(0.132)
Near San Francisco (=1)	1.103	1.017	0.085***	0.072***	1.246***	1.132
	(0.129)	(0.873)	(0.000)	(0.000)	(0.000)	(0.178)
IPO volume$_{t-1}$	1.924***	1.481**	0.038***	0.033***	1.926***	1.506**
	(0.000)	(0.022)	(0.000)	(0.000)	(0.000)	(0.014)
EW IPO first day returns$_{t-1}$	0.263***	0.295***	−0.035***	−0.022**	0.262***	0.295***
	(0.000)	(0.000)	(0.000)	(0.028)	(0.000)	(0.000)
Real GDP growth$_{t-1}$	3.723	1.480	−0.094***	−0.067***	3.985	1.515
	(0.342)	(0.857)	(0.000)	(0.001)	(0.311)	(0.848)
EW market returns$_{t-3 \text{ to } t-1}$	9.177***	5.843***	−0.001	0.003	8.845***	5.742***
	(0.000)	(0.000)	(0.734)	(0.684)	(0.000)	(0.000)
Aggregate MB$_{t-1}$	0.238***	0.533**	−0.056***	−0.055***	0.244***	0.524**
	(0.000)	(0.044)	(0.000)	(0.000)	(0.000)	(0.029)
Credit spread$_{t-1}$	1.598***	1.664***	−0.002	−0.008***	1.619***	1.659***
	(0.000)	(0.000)	(0.276)	(0.008)	(0.000)	(0.000)
Federal funds rate$_{t-1}$	0.844***	0.874**	−0.013***	−0.012***	0.841***	0.868**
	(0.000)	(0.013)	(0.000)	(0.000)	(0.000)	(0.011)
Observations	115,230	44,268	115,230	44,268	115,230	44,268
Pseudo R^2	0.02	0.02	0.08	0.05		
First-stage F-statistic			388.70	89.91		

Panel B: Industry organization capital intensity						
	Quarters to exit		Org. capital		Quarters to exit	
	Cox		First stage		2S control function Cox	
	All	Large	All	Large	All	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Z_{jt}^{Org}			0.076***	0.071***		
			(0.000)	(0.000)		
Organization capital intensity$_{t-1}$	0.273***	0.075***			0.098***	0.048***
	(0.000)	(0.000)			(0.000)	(0.000)
Organization capital intensity residual					11.726***	18.370***
					(0.000)	(0.000)
Ln(Industry funding flow)$_{t-1}$	0.919**	1.025	0.010***	0.013***	0.970***	0.973***
	(0.021)	(0.691)	(0.000)	(0.000)	(0.000)	(0.000)
Total q$_{t-1}$	1.059**	1.072*	0.032***	0.030***	1.062***	1.074***
	(0.014)	(0.057)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Assets)$_{t-1}$	1.311***	1.178	0.009***	−0.002	0.970***	0.930***
	(0.000)	(0.156)	(0.000)	(0.590)	(0.000)	(0.000)
Cash/total assets$_{t-1}$	11.557***	8.295***	0.005	−0.056	0.857***	0.797***
	(0.000)	(0.007)	(0.799)	(0.119)	(0.001)	(0.009)
COGS/total assets$_{t-1}$	3.412*	3.042	0.971***	0.872***	3.420***	6.156***
	(0.094)	(0.330)	(0.000)	(0.000)	(0.000)	(0.000)
Loss firm$_{t-1}$	2.322***	2.444**	−0.055***	−0.043***	0.762***	0.734***
	(0.001)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Age)$_{t-1}$	6.898***	11.364***	0.129***	0.130***	2.317***	2.281***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry Private MB$_{t-1}$	6.577***	10.422**	−0.044*	−0.025	1.878***	2.055***
	(0.002)	(0.021)	(0.064)	(0.462)	(0.000)	(0.000)
Scale (=1)	1.100	1.067	0.016***	0.018***	0.856***	0.865***
	(0.142)	(0.516)	(0.000)	(0.000)	(0.000)	(0.000)
Near San Francisco (=1)	1.087	0.979	0.013***	0.012***	1.045***	1.017*
	(0.197)	(0.834)	(0.000)	(0.001)	(0.000)	(0.088)
IPO volume$_{t-1}$	1.764***	1.447**	−0.005***	−0.004***	1.328***	1.372***
	(0.000)	(0.027)	(0.000)	(0.007)	(0.000)	(0.000)
EW IPO first day returns$_{t-1}$	0.265***	0.331***	0.041***	0.054***	0.527***	0.433***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth$_{t-1}$	7.679	2.416	−0.161***	−0.151***	0.818	0.760
	(0.110)	(0.655)	(0.000)	(0.000)	(0.201)	(0.300)
EW market returns$_{t-3 \text{ to } t-1}$	8.088***	5.200***	−0.025***	−0.028***	1.966***	2.099***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Aggregate MB$_{t-1}$	0.227***	0.463**	−0.036***	−0.031***	0.253***	0.212***
	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)
Credit spread$_{t-1}$	1.313***	1.244	−0.030***	−0.027***	0.668***	0.633***
	(0.001)	(0.105)	(0.000)	(0.000)	(0.000)	(0.000)
Federal funds rate$_{t-1}$	0.834***	0.865**	0.000	0.001	0.707***	0.677***
	(0.000)	(0.011)	(0.854)	(0.366)	(0.000)	(0.000)
Observations	115,230	44,268	115,230	44,268	115,230	44,268
Pseudo R^2	0.02	0.03	0.49	0.46		
First-stage F-statistic			558.74	185.68		

Table 8. Summary statistics for the matched IPO sample in the year before IPO

The table reports summary statistics on the offer characteristics of IPOs, the financial characteristics of firms immediately before their IPO, and on the governance and control mechanisms of firms at their IPOs. In Panel A, the sample consists of 307 large IPOs between Q1 2010 and Q4 2024, and for each large IPO, the nearest neighbor VC-backed IPO based on firm pre-large startup round year, headline valuation, funds raised, and age using propensity scores. In Panel B, the sample consists of 102 large IPOs with dual-class shares and 212 large IPOs without dual-class shares, respectively. In Panel C, the sample consists of 308 large IPOs between Q1 2010 and Q4 2024, and for each large IPO, the nearest neighbor young public firm based on IPO valuation. In all panels, Column (7) reports differences in means between large startup IPOs and the nearest neighbor small startup IPOs. Column (8) reports differences in medians between unicorn IPOs and the nearest neighbor small startup IPOs. The stars correspond to t-tests (Wilcoxon tests) of differences in means (medians). Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively.

Panel A: Large startups that IPO matched to other startups

	Large startups			Matched controls			Differences	
	Obs (1)	Mean (2)	Median (3)	Obs (4)	Mean (5)	Median (6)	Means (7)	Medians (8)
IPO valuation ($ millions)	307	2,497.07	886.58	230	491.21	360.11	2,005.87***	526.47***
Offer price above range	307	0.48	0.00	230	0.27	0.00	0.21***	0.00***
Fraction of proceeds to selling shareholders	307	0.05	0.00	230	0.01	0.00	0.04***	0.00***
First-day return	307	0.37	0.29	230	0.22	0.10	0.15***	0.19***
Three-month return	307	0.41	0.25	230	0.26	0.16	0.15**	0.09**
Six-month return	307	0.16	0.13	230	0.13	0.08	0.03	0.04
Total assets	299	383.29	156.10	224	74.87	44.76	308.43***	111.34***
Cash and STI/total assets	298	0.59	0.60	224	0.71	0.81	−0.12***	−0.21***
CAPX/total assets	295	0.05	0.02	222	0.04	0.01	0.00	0.01**
R&D/total assets	299	0.31	0.20	224	0.69	0.42	−0.38***	−0.22***
SG&A/total assets	299	0.33	0.22	224	0.28	0.15	0.05*	0.07**
COGS/total assets	295	0.33	0.19	222	0.31	0.00	0.02	0.19***
Share of organization capital employees	294	0.37	0.34	216	0.22	0.20	0.15***	0.15***
Gross profit/total assets	295	0.23	0.12	222	−0.05	0.00	0.28***	0.12***
Negative net income (=1)	307	0.88	1.00	230	0.93	1.00	−0.06**	0.00**
Dual class shares (=1)	307	0.33	0.00	230	0.04	0.00	0.29***	0.00***

Panel B: Large startups with and without dual shares								
	Dual class			Single class			Differences	
	Obs	Mean	Median	Obs	Mean	Median	Means	Medians
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IPO valuation ($ millions)	102	3,411.65	857.29	212	2,124.68	897.83	1,286.97	−40.54
Offer price above range	102	0.65	1.00	212	0.39	0.00	0.26***	1.00***
Fraction of proceeds to selling shareholders	102	0.08	0.00	212	0.04	0.00	0.04**	0.00***
First-day return	102	0.39	0.33	212	0.35	0.26	0.04	0.07
Three-month return	102	0.36	0.21	212	0.42	0.26	−0.06	−0.04
Six-month return	102	0.12	0.10	212	0.17	0.12	−0.06	−0.02
Total assets	101	656.81	268.26	204	318.00	122.89	338.82***	145.37***
Cash and STI/total assets	100	0.52	0.55	204	0.62	0.68	−0.10***	−0.13***
CAPX/total assets	100	0.05	0.03	201	0.04	0.02	0.00	0.01*
R&D/total assets	101	0.19	0.16	204	0.37	0.23	−0.18***	−0.07***
SG&A/total assets	101	0.44	0.43	204	0.28	0.15	0.16***	0.28***
COGS/total assets	100	0.38	0.23	201	0.29	0.16	0.09*	0.06***
Share of organization capital employees	97	0.49	0.53	201	0.31	0.26	0.18***	0.28***
Gross profit/total assets	100	0.41	0.41	201	0.14	0.00	0.27***	0.41***
Negative net income (=1)	102	0.84	1.00	212	0.88	1.00	−0.04	0.00

Panel C: Large startups matched to young public firms on IPO valuation								
	Large startups			Matched controls			Differences	
	Obs	Mean	Median	Obs	Mean	Median	Means	Medians
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total assets	308	417.14	157.84	235	1,497.73	329.39	−1,080.59***	−171.55***
Sales	304	227.06	79.60	224	800.97	162.34	−573.91***	−82.74***
Cash and STI/total assets	307	0.58	0.60	228	0.33	0.18	0.25***	0.42***
PP&E/total assets	308	0.11	0.07	233	0.17	0.06	−0.06***	0.00
CAPX/total assets	304	0.04	0.02	224	0.04	0.02	0.00	0.00**
R&D/total assets	308	0.30	0.20	235	0.16	0.01	0.14***	0.19***
SG&A/total assets	308	0.32	0.22	235	0.23	0.10	0.09***	0.12***
Long-term debt/total assets	302	0.15	0.02	235	0.26	0.08	−0.11***	−0.07***
COGS/total assets	304	0.32	0.19	224	0.47	0.26	−0.15***	−0.07***
Gross profit/total assets	304	0.23	0.13	224	0.28	0.20	−0.05	−0.06**
Negative net income (=1)	308	0.90	1.00	235	0.52	1.00	0.38***	0.00***
Dual class shares (=1)	308	0.33	0.00	235	0.23	0.00	0.09**	0.00**

Appendix. Variable definitions

This appendix contains detailed definitions of dependent and independent variables used in the analysis. Compustat data mnemonics are in italics within parentheses.

Variable name	Description
Dependent variables	
Large status	An indicator variable that equals one from the quarter a startup reached a post-money headline valuation of at least \$300 million until the end of the sample and zero otherwise.
Independent and other variables	
Aggregate MB	The equally weighted average of the market value of common equity (*ceqq*) divided by book value of equity (*cshoq*×*prccq*) across all public firms in a quarter.
Cash/total assets	Cash (*chq*) divided by assets (*atq*).
CAPX/total assets	Capital expenditures (*capxy*) divided by assets (*atq*).
Credit spread	The spread between the yield of Baa-rated corporate bonds and 10-year treasuries at the end of a quarter.
Ex ante weak-NCA	An indicator variable that equals one if the startup's state has an NCA enforceability score, obtained from Golubov and Zhong (2024), below the sample median before the enactment of the DTSA.
EW IPO first day returns	The difference between the first closing price and the offer price, divided by the offer price, averaged across all firms that went public in a quarter.
EW market returns	Compound monthly returns on the equally weighted index in a quarter.
Exit MB	The ratio of the valuation at exit (DLs, IPOs, SPACs, M&As, failures) to the total equity funding.
COGS/total assets	Cost of goods sold (*cogsq*) divided by total assets (*atq*).
Federal funds rate	The effective federal funds rate at the end of a quarter.
Fixed assets/total assets	Fixed assets (*ppentq*) divided by assets (*atq*).
IPO volume	The total number of IPOs, excluding penny stocks, units, and closed-end funds, divided by the total number of listed firms in a quarter.
Ln(Age)	The natural log of age. Age is calculated as the number of years since the minimum of the first year a firm appears in CRSP and the first year a firm appears in Compustat.
Ln(Assets)	The natural log of assets (*atq*).

Ln(Industry funding flow)	The natural log of aggregate funding flows, calculated as the sum of the total amount of funding in an industry-quarter provided to VC-backed startups with more than \$50 million in cumulative funding in the CB insights database.
Loss firm	The percentage of firms in an industry-quarter with negative net income.
Near San Francisco (=1)	An indicator variable that equals one if a startup's headquarter is within 200 miles of San Francisco.
Organization capital intensity (Industry)	The ratio of organization capital to the sum of knowledge and tangible capital. Organization capital is the capitalized fraction (γ) of selling, general, and administrative expenses (SG&A, *xsgaq*). Knowledge capital is capitalized research and development expenses (R&D, *xrdq*). Tangible capital is capitalized capital expenditures (*capex*). The capitalization rate for R&D and the fraction of SG&A expenses that contribute to investment in organization capital are industry-specific, and obtained from Ewens, Peters, and Wang (2024). The annual depreciation rate for organization capital is 20%, as in Ewens, Peters, and Wang (2024), and the annual depreciation rate for *capex* is 10%.
Organization capital intensity (LinkedIn)	The fraction of employees in selected managerial positions (e.g., product managers), technical and engineering roles (e.g., software engineers, IT specialists, system architects), and creative positions (e.g., product design).
Post DTSA	An indicator variable that equals one after the enactment of the Defend Trade Secrets Act in Q2 2016.
Private market MB	The ratio of the post-money valuation after a specific funding round, divided by the cumulative amount of equity funding raised up to and including that round.
Real GDP growth	The quarterly growth rate of real GDP.
R&D/total assets	Research and development expenses (R&D, *xrdq*) divided by assets (*atq*). If R&D is missing, it is set equal to zero.
Scale (=1)	An indicator variable that equals one if the words "platform," "network," or "connect" appear in the textual description of a firm's business in CB Insights.
SG&A/total assets	Selling, general, and administrative expenses (SG&A, *xsgaq*) minus research and development expenses (R&D, *xrdq*) and in-process R&D (*rdipq*) divided by assets (*atq*). If SG&A, R&D, or in-process R&D are missing, they are set equal to zero. If R&D excess SG&A but is less than COGS, or if SG&A is missing, we do not subtract R&D and in-process R&D from SG&A.
Total *q*	The market value of common equity (*cshoq*×*prccq*) plus the book value of debt (*dltt*+*dlc*) minus current assets (*act*) divided by the sum of the book value of property, plant, and equipment (*ppegt*) and the replacement cost of intangible capital (Peters and Taylor, 2017).