Founder Factories: The Origins of High-Growth Startups

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Abstract

Using global worker-level data from Revelio Labs matched to startup and financing databases, we examine whether some organizations systematically produce founders who build large, internationally scalable startups. We show that the production of such founders is highly concentrated and that employers differ substantially, even after adjusting for parent size, in the scale and international footprint of the ventures created by their former employees. To distinguish selection from organizational exposure, we exploit corporate acquisitions that reassign employees to new firms. Employees exposed to employers with stronger records of producing scalable startups later found ventures that are larger, more geographically dispersed, and more likely to grow through acquisitions. The results suggest that organizational environments shape not only who becomes a founder, but also the kind of venture that founders build.

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1 Introduction

A small fraction of startups accounts for a disproportionate share of job creation and innovation (Decker, Haltiwanger, Jarmin, and Miranda, 2014; Botelho, Fehder, and Hochberg, 2026). A central question in entrepreneurial finance is therefore where scalable startups come from. While prior work has made substantial progress in explaining who enters entrepreneurship, we know much less about why some founders build ventures that scale in employment, geographic scope, and acquisition activity whereas others do not. We ask whether part of this heterogeneity is shaped by founders' prior employers.

Anecdotes—from the "PayPal mafia" to alumni networks associated with firms such as Google, McKinsey, and Goldman Sachs—suggest that some employers are unusually effective at producing founders of high-growth startups. Consistent with this view, Gompers, Lerner, and Scharfstein (2005) show, for U.S. public corporations over 1986–1999, that employees' entry into venture-backed entrepreneurship is highly concentrated across parent firms. We build on this insight, but focus on a different margin: conditional on becoming a founder, which prior employment environments are associated with building ventures that scale in size and scope, and why?

We examine a mechanism that has received little direct attention in the literature: exposure to certain organizations may tilt would-be entrepreneurs toward projects designed to scale. To study this question, we use worker-level data covering hundreds of millions of employment histories globally. We identify founders and their last employer before startup creation, which we refer to as the startup's *parent*. We measure startup success using outcomes that capture scalability: employment at and after founding, growth in the first years, the geographic dispersion of the workforce, and acquisition activity. We refer to employers with an unusually strong tendency to produce founders of scalable startups as *founder factories*.

Our analysis yields three main results. First, we confirm that the production of founders of scalable startups is highly concentrated worldwide among a relatively small set of organizations. A few large technology, consulting, and financial firms generate thousands of startups founded by former employees, and these startups account for a disproportionate share of startup employment a few years after founding. Second, there is substantial heterogeneity across parents in the scale of the startups created by their alumni, even after controlling for the mechanical role of parent size. We capture this heterogeneity with parent fixed effects that measure the average size of alumni-founded startups three years after founding, controlling for founder-country, parent-industry, and cohort fixed effects. Third, startups founded by alumni of high fixed-effect parents look systematically different: they start larger, internationalize earlier, hire more technical workers, and are more likely to grow through acquisitions.

These patterns can reflect several mechanisms. One is **selection and certification**: high-ability individuals may sort into particular firms, and investors may treat an employer's brand as a signal of founder quality. A second is **acquired knowledge and networks**: employees may learn transferable skills and build relationships that directly facilitate entrepreneurship. A third, which is the mechanism we emphasize, is **ambition to scale**. Some organizations may shape the

aspirations of their employees and the kinds of projects they pursue. The culture of the parent firm may tilt founders toward globally scalable strategies, such as avoiding niche projects tied to local idiosyncrasies, hiring rapidly, or internationalizing early. This mechanism is distinct from knowledge transfer: it concerns founders' objectives and reference points, not only what they know.

A central challenge in separating organizational exposure from selection is endogeneity. To address it, we exploit corporate acquisitions that reassign employees to new organizational environments. We focus on mid-level employees of acquired firms, excluding founders and top management, and retain those who remain with the acquirer for at least one year. We then compare the subsequent startups founded by employees exposed post-acquisition to high fixed-effect acquirers with those founded by employees exposed to low fixed-effect acquirers. Because acquisition decisions are unlikely to be driven by the latent entrepreneurial potential of mid-level target employees, this design provides plausibly exogenous variation in organizational exposure. The acquisition-based estimates are consistent with exposure to founder factories increasing the scale and international footprint of the ventures later created by these employees. The effects are stronger the longer employees remain with the acquirer after the acquisition. These patterns are difficult to reconcile with a pure certification story and are consistent with an exposure mechanism that accumulates over time.

The paper makes two contributions. First, we provide a global, size-adjusted measure of employer-level founder-factory intensity—an employer's propensity to produce founders of ventures that become large and internationally present. Second, we provide evidence consistent with a causal effect of organizational exposure on subsequent startup scale and international footprint. More broadly, the results suggest that the supply of scalable entrepreneurial projects depends not only on founder traits and investor selection, but also on the organizational environments in which future founders work.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature and positions our contribution. Section 3 describes the construction of the founder-startup-parent panel from Revelio and the mapping to startup, funding, and patent datasets, along with our measures of scale and international footprint. Section 4 documents concentration in founder production and estimates parent fixed effects that capture founder-factory intensity net of parent size. Section 5 characterizes how startup attributes and outcomes vary with founder-factory intensity, including initial scale, international dispersion, workforce composition, and acquisition activity. Section 6 presents the acquisition-based research design and the corresponding evidence, including tenure gradients and tests that speak to certification and imitation. Section 7 concludes and discusses implications for firms, investors, and policy.

2 Literature Review

The closest antecedent is Gompers et al. (2005), who study "entrepreneurial spawning" from U.S. public corporations. They document that entry into venture-backed entrepreneurship is highly

concentrated across parent firms and relate that variation to parent characteristics and local entrepreneurial conditions. Habib, Hege, and Mella-Barral (2013) also study the determinants of spawning intensity. Our paper differs in three ways. First, our object is not entry into entrepreneurship per se, but the *scalability* of the ventures founders create. Second, we use global worker histories and recent cohorts rather than a narrower set of parents and a single financing category. Third, we explore the idea that exposure to certain organizations may shape the ambitions and project choices of future entrepreneurs, and we use acquisitions to generate plausibly exogenous variation in such organizational exposure.

Our results also relate to work on employee entrepreneurship and spinouts. Klepper (2007) emphasizes knowledge inheritance from parent firms. Gompers, Kovner, Lerner, and Scharfstein (2010) and Lazear (2005) highlight the role of founder traits and entrepreneurial human capital. Babina and Howell (2024) show that corporate R&D increases employee departures to startups, and Kwan, Matthies, Townsend, and Xu (2025) show that remote work raises entrepreneurial spawning. We complement this literature by focusing on a different margin: among those who become founders, which prior employers are associated with building ventures that scale, and whether that relation reflects causal exposure. More broadly, our focus on scalable startups fits within the innovation-driven entrepreneurship literature reviewed by Botelho et al. (2026). A related line of work studies how labor-market risk and insurance shape entry into entrepreneurship and the composition of founders. Using a large French reform, Hombert, Schoar, Sraer, and Thesmar (2020) show that expanding unemployment-insurance protection increases business creation without lowering average entrant quality, consistent with downside insurance relaxing constraints that deter high-potential founders. Complementing this evidence, Hacamo and Kleiner (2022) show that adverse labor-market conditions at labor-market entry raise entrepreneurship ("forced entrepreneurship"), but the marginal entrepreneurs induced by weak conditions are not of lower quality on average. Our paper is orthogonal: holding fixed the decision to become a founder, we ask whether prior *organizational environments* shape the *scale* and international ambition of the ventures founders build.

A related concern in entrepreneurial finance is whether venture outcomes reflect investor selection, investor certification, or investor value added. Hsu (2004) and Hellmann and Puri (2002) document certification and professionalization roles of venture capital. Hochberg, Ljungqvist, and Lu (2007) and Bernstein, Giroud, and Townsend (2016) show that investor networks and monitoring matter for venture outcomes. These mechanisms map naturally into our selection and certification channel. Our acquisition-based design helps separate them from organizational exposure. Finally, our emphasis on ambition to scale connects to work on organizational capital. Bloom and Van Reenen (2007) link management practices to firm performance, and Guiso, Sapienza, and Zingales (2015) show that corporate culture can be an economically meaningful asset. Our results suggest that one manifestation of organizational capital is the ability to shape employees' growth benchmarks and the types of ventures they attempt to build. Methodologically, our acquisition setting is also related to Kim (2024), who shows that workers brought in through acquisitions behave differently from regular hires.

3 Data and sample

3.1 Data

We use several data sources for our analysis. Our primary source of information are firm founders. We identify them through RevelioLab, a workforce database. We collect firm-levvel information from Tracxn and Preqin and patent data from Google Patents.

3.1.1 RevelioLabs

Our worker-level data come from Revelio Labs, a workforce database. The dataset is mostly based off of people's LinkedIn profiles and contains information such as employment history, job titles and predicted salary (Jiang, Tang, Xiao, and Yao, 2025). Individual's education and skills are also available and can be aggregated to the company level. The Revelio snapshot we use is from December 2004 and therefore covers all individuals with a Linkedin profile at that time. The number of unique individuals included is 770,137,867. LinkedIn's user base exhibits significant demographic skews, with college-educated individuals and white-collar professionals maintaining profiles at substantially higher rates than those without higher education or in blue-collar occupations. This sampling characteristic makes our dataset especially valuable for studying professional and educational outcomes among college-educated, white-collar populations (Amanzadeh, Kermani, and McQuade, 2024).

3.1.2 Tracxn

We complement RevelioLabs with Tracxn, a market-intelligence platform covering more than 350,000 private firms globally in more than 250 sectors. Tracxn provides startup-level information on acquisition outcomes, business models, operating sectors, funding rounds and investors. We use Tracxn's acquisition database from 2005 to 2024 to track acquisitions over time. Information includes acquirer, target, deal date or deal type.

3.1.3 Preqin

We obtain startup-level financing data from Preqin, a provider specialized in alternative assets markets. Preqin aggregates private-market investment information from public disclosures (including FOIA-based pension records), regulatory filings, and general-partner reporting (Begenau and Siriwardane, 2024). We use these data to measure funding amounts, investor participation, and financing timing for startups in our sample.

3.2 Sample Construction

Our objective is to identify startups in the RevelioLabs dataset. To do so, we identify firm founders from individuals' job titles in RevelioLabs. We search for terms identifying founders in thirteen distinct languages that commonly appear in RevelioLabs (e.g. "founder" or "fondateur") and we

eliminate noisy titles such as "Chief of Staff to the Founder" or "Executive Assistant to the Founder's Office" (See Appendix 9.1).

To ensure that individuals identified as founders from their job titles are indeed involved in the firm creation, we eliminate those who are not among the first ten employees of the firm according to RevelioLabs. We also remove any parent firm or startup that are identified with noise such as "Stealth Mode Startup", "Various Companies" or "Freelance" (Section 9.1). We then use founders and startups obtained from the previous step and extract two more types of information. First, we extract from RevelioLabs the integral employment history of each founder. This allows us to investigate the corporate and institutional origins of startup founders. In particular, this allows us to identify *parent companies*, that is, firms for which founders worked before creating their startups.[1] Second, for each startup in the sample, we extract every user who has current or prior work experience at the startup. This allows us to compute annual- and firm-level outcomes such as annual employee count or annual employee growth rate. Furthermore, to ensure that the sample has a good coverage, we keep startups that are founded after 2010.[2] Finally, we eliminate startups created by founders who were holding internship positions and any positions lasting less than six months at their former employer.

Table 1 presents summary statistics for every startups created between 2010 and 2024. The typical startup in our general sample has two (2.67) employees at initiation and is founded by a single founder (1.39). The typical founder in our general sample has occupied six (6.76) positions pre-startup in three (3.30) different firms in a single (1.40) country. The founder typically starts her startup (86%) in the same country in which she was employed pre-startup. Finally, the average level of hierarchy pre-startup is high (5 out of 7, where 1 is low and 7 is high). The typical firm from hailing a founder is a private firm (91%) which was founded in 1989 with an average employee count of 9,846 employees.

4 Descriptive results

4.1 The origin of startups

Table 2 presents the 30 firms that spawn the most startups over our sample period, ordered by their total number of startups created. This list is dominated by firms located in the U.S.: the 15 biggest startup generators are large U.S. companies, from Microsoft (4,256 startups generated) to Citigroup (1,349 startups generated). Most of the biggest spawners are companies in the tech, banking and consulting industries, with a few exceptions like the U.S. Army. Startup creation is also heavily skewed: Micrsosoft, which dominates the ranking, generates more than four times as many startups as the French consulting firm Capgemini, ranked 30, and about 2,240 times as many startups as the average among the 1,248,790 spawners generating at least one startup from 2021 to

[1] In the rest of the paper, we use the terms *parent company*, *mother company* or *spawner* indifferently to refer to these firms.

[2] 2010 is the year from which "LinkedIn shifts into hyper-growth mode, reaching 90 million members" (LinkedIn Press release).

2024, which stands at about 1.9 startup. Column 3 shows that startups generated by the biggest spawners employ a disproportionately large number of employees five years after their creation. For example, the five largest spawners generate 0.16% to 0.22% of the total number of startups, which employ in total from 0.36% to 0.57% of the total number of employees working for startups five years post-creation.

Figure 1 shows the number of startups created by country, each country representing the location of parent firms in our sample, as well as the total number of jobs in these startups three years after their creation. It is heavily dominated by the U.S.: Almost 47% of startups and 38% of the three-year forward employment they generate in our sample are created by individuals whose previous employment was in U.S. headquartered firms. The second largest provider of startups, Great-Britain, accounts for around 9% of startup creation (and 6% fo three-year forward employment) and no other country accounts for more than 5%.

Figure 2 shows the industry distribution of parent firms. It is dominated by the financial service industry, with about 11% of startups created by individuals working in financial services before creating their firm. This is consistent with the presence of banks in the top parent companies in Table I. Some tech sectors also account for a significant fraction of parent companies. Consulting firms, whose overall weight in the economy is more limited, do not appear in this figure although some firms in this industry generate many startups, as discussed previously.

4.2 Calculating *parent firm fixed effects*

Table 3 examines the parent-level determinants of spawning and startup growth. In the first four columns, we regress the number of startups created and, in columns 5 to 8, their three-year forward aggregate number of employees. The size of the mother firm, measured by its number of employees and its propensity to grow through acquisitions, is an important determinant of both measures in columns 1 and 4, in which we use all parent firms. When we restrict the sample of parent firms to listed companies (in columns 4 and 8), the size of the company measured by its market capitalization is also an important determinant of the firm's generation of startups and of high-growth startups, i.e., startups with a greater number of employees three years post-creation. Firms founded after 1990, firms with a greater workforce dispersion across countries and with more STEM employees are also more prone to generate startups and high-growth startups. Firms with a larger fraction of employees with MBA and PhD degrees generate more high-growth startups. Finally, firms with a positive log growth in terms of their scope of operations between 2005 and 2010 as defined by Hoberg and Phillips (2025) are also more prone to generate startups and high-growth startups between 2010 and 2024.

Next, we construct a firm-level measure of high-growth startup generation. This measure, which we call *parent firm fixed effect*, captures the average size of startups created by former employees of the focal firm three years after their creation, controlling for the size of the focal firm. To remove noise, we remove from the sample startups whose founder worked for a small firm, i.e., a firm

with less than 1,630 employees on average between 2010 and 2019, before founding the firm[3]. To measure these fixed effects, we use the following regression specification:

$$y_{f,i,j,k} = \gamma_j + c_f + s_k + \delta X_i + \epsilon_{f,i,j,k} \tag{1}$$

where: $y_{f,i,j,k}$ is the total number of employees at startup i, created by founder f who used to work for mother company j in industry k, three years after the startup creation. γ_j is the fixed effect of the spawner j of startup i, c_f is the country where founder f is located when starting startup i, s_k is the industry of spawner j, $X_{i \leftarrow j}$ is a vector of startup-level controls: year of incorporation, number of founders. We estimate regression (1) on 220,593 founder-startup-spawner triplets. We control for the parent firm industry k (NAICS) since startup industry is missing most of the time. Furthermore, we control for the country of location of the founder when she creates the startup. We use a Poisson regression specification since the outcome is a count-like variable.

We then purge the estimated spawner fixed effects from any mechanical scaling effect arising from the size of the mother company. To do so, we regress the fixed effects associated to spawner j on the log of j's average employee count from 2010 to 2019. The resulting residuals are the spawner fixed effects adjusted for the size of the spawner. The regression specification is the following:

$$\hat{FE}_j = \beta_0 + \beta_1 \times \log(1+\text{EmployeeCount}_j) + \epsilon_j \tag{2}$$

where $\hat{FE}_j$ is the fixed effect associated to spawner j and $EmployeeCount_j$ is the average employee count of spawner j from 2010 to 2019, estimated from RevelioLabs.

Table 4, which presents the 30 largest parent firms in the top 10% of size-adjusted fixed effects (the ϵ_j from Equation (2)) shows some overlap with the 30 firms that generate the most startups as seen in Table 2. Four of the 30 largest firms with the top 10% of size-adjusted fixed effects are also part of the 30 biggest spawners from Table 2.

Figure III shows the country distribution of parent firms in the top 25 percent of the parent fixed effect distribution. As is the case for the number of startups generated and their total number of employees, the U.S. concentrate a large fraction of spawners of growth companies. Almost 40% of these parent firms are located in the U.S., compared to 5% to 10% in Great-Britain, India and France, and less than 5% in any other country.

An implicit assumption is that parent firm fixed effects capture a fundamental firm-level characteristic, i.e., the propensity of the firm's alumni to create scalable startups. If they do, then parent fixed effects should be persistent over time. To verify this, for each year T between 2015 and 2021 we calculate parent fixed effects using data from 2010 to year $T-1$. We then calculate, for each parent firm, the total number of jobs in startups created by the firm's employees at the end of year $T+3$. Figure 3 presents the resulting plot. Each year, we breakdown firm fixed effects into vigintiles and for each vigintile, we plot the total number of jobs created by startups spawned

[3]This figure corresponds to the 99th percentile of the distribution for parent firms generating at least one startup. By contrast, the same 99th percentile for firms generating zero startup is 45.5 employees.We do not go beyond 2019 to avoid any noise coming from the COVID-19 shock.

by parent firms at $T+3$. The figure shows a sharp and monotonic relation between parent firm fixed effects based on job creation by startups spawned in past years and future job creation by this year's startups, confirming that parent fixed effects capture a fundamental firm-level characteristic.

To understand whether parent companies that are more prone to generate high-growth startups generate startups with different characteristics than the typical startup, we next regress some characteristics of startups on the fixed effect of their parent firm constructed previously, as well as other controls such as the number of founders and their experience when they create their startup, equal to the number of positions the founder occupied before founding her startup (averaged across all founders). A single startup is characterized by the average parent firm fixed effect of its founder(s). Table 5 displays the results. It shows that startups created by former employees of firms that generate high-growth startups (i.e., with large fixed effects) tend to be larger at birth, to be more dispersed geographically, i.e., to hire employees in more countries (See Appendix 9.2 and 9.2.2).

In columns (4) to (6) of Table 5, we explore the evolution of startups as a function of the size-adjusted fixed effects of their parents. The table shows that startups created by former employees of firms with larger fixed effects are more likely to acquire and do more acquisitions on average (as of 2025). Consistent with the view that they are riskier than the average startup, they are also more likely to experience both very favorable outcomes (i.e., acquisition) and very unfavorable ones, i.e., they are more likely to fail after three years. Results are comparable when standard errors are bootstrapped (since we use a generated regressor) (Table 19).

5 Instrumented tests

5.1 Acquisitions by parent firms as a shock to the career paths of employees

These findings may reflect endogenous matching of high-growth firms and individuals with the potential to create high-growth startups. Instead, our goal is to ask whether some firms instill in their employees an ambition that, when they later found their own companies, drives them to pursue rapid growth, irrespective of their intrinsic characteristics. To test this, we need to break the potentially endogenous link between firms that generate startups and the characteristics of the employees that transition from these firms to startup creation. To do so, instead of considering employees of high-fixed-effect companies, we consider employees of firms that they acquire. Our assumption is that acquisition decisions of high-fixed-effect firms are independent of the characteristics of the employees of the firms they acquire, at least of employees below top ranks (in practice, we only consider target employees with hierarchical ranks 1 to 5 in Revelio and exclude employees with ranks 6 and 7).

We create a sample of employees who were carried over to an acquiring firm and are, therefore, exposed to the acquiring firm's culture. To identify these employees, we focus on business z acquired by acquirer j between 2005 to 2020. We call such carried-over employees *alumni employees* of target firm z acquired by firm j. Using the fixed effects calculated to evaluate the ability of mother

companies to generate high-growth startups, we then study the heterogeneity between startups created by employees carried over to high fixed-effect acquiring firms versus employees carried over to the rest of firms.

Examples of startups that are in our final sample are Mill Industries Inc., co-founded in 2020 by Harry Tannenbaum, six years after Nest Labs was acquired by Google in 2014. Harry Tannenbaum stayed at Nest Labs from 2012 to 2018 before moving to Google as a Director in charge of hardware from 2018 to 2020 and finally launching Mill in 2020. Other examples include Digital Medical Tech, LLC, founded in 2016 by Matthew Nicholson, four years after DePuy Synthes was acquired by Johnson & Johnson, XDBS Corporation, which was founded in 2011 by Kartik Anand, three years after he left Digitas which was acquired by Publicis Group in 2006. Other examples include Rubrik, Inc, co-founded by Arvind Nithrakashyap four years after he left Purisma in 2010 which was acquired by Dun & Bradstreet in 2007.

A given startup is characterized by the average of the fixed effects of the acquiring firm j that its founders were carried-over to. We impose founders to stay at least two years on average post-acquisition to ensure they are exposed to the culture of the acquiring firm.[4] In subsequent analyses, we re-estimate parent firm fixed effects as in equations (1) and (2) above, but excluding startups created by *alumni employees* who used to work at firms acquired by parent companies to avoid contamination of the fixed effects by the variables of interest explored in later tests.

We compute z-scores by normalizing parent fixed effects. In our baseline analysis, we ask whether parents' z-scores are related to the probability for alumni of the parent firm to become entrepreneurs and to the characteristics of the startups they create.[5]

5.2 Results

First, we present visual univariate evidence on the link between parent firm fixed effects and characteristics of the startups their employees create. In Figure 4, we breakdown parent firms into deciles depending on their fixed effects and for each decile, we plot the average of selected outcome variables from Table 5 for spawned startups three years after their creation. The figure shows a sharp monotonic relation between parent firms' z-scores and most measures of growth or scale of the startups.

Next, we provide a similar analysis in a multivariate context. First, in Table 6, we estimate the probability for alumni employees to found a startup in the three years following the acquisition of the firm they work for depending on the z-score of their parent firm. We control for employee-

[4]This manipulation removes cases like Cruise LLC (autonomous vehicle), which was co-founded by Daniel Kan in 2014, months after Exec (W12), co-founded by Kan himself, was acquired by Handy (2014). Another of such example is Picnic Technologies, which was co-founded by Bas Verheijen in 2011, months after he departed from his role as Marketing & Format Director at C1000, following its acquisition by Jumbo (2011).

[5]In alternative tests that appear in the appendix, we breakdown parent companies by their estimated fixed effect and we call those with fixed effects above the median *prolific spawners*. We then assign startup founders to a treatment and a control group depending on whether the firms they used to work for were acquired by prolific vs. non-prolific spawners. We re-estimate the outcomes of startups depending on whether their founder is an alumni from a prolific or a non-prolific spawner.

level characteristics at the time of acquisition: *seniority*, taken from RevelioLabs and taking values from 1 (low) to 7 (high), proxies for the individual's position in the hierarchy. *experience* is the number of positions the individual has occupied since they appear in RevelioLabs. We also include *country* × *year*, *industry* × *year* and *country* × *industry* fixed effects to control for country and industry unobservables. The table shows that alumni acquired by prolific spawners are more likely to become entrepreneurs, by about 0.07% on average. This represents xxx% of the standard deviation of the annual probability of creating a startup for individuals in our sample of alumni. This effect is also statistically significant at the 5% level. Results are economically and statistically similar whether we consider three-year forward entrepreneurship probability (Is Founder$_{t+3}$) or five-year forward entrepreneurship probability (Is Founder$_{t+5}$; Table 20) as well as when standard errors are bootstrapped (since we use a generated regressor) (Table 21).

Next, we ask whether the characteristics of startups created by alumni depend on the type of parent firm they are exposed to post-acquisition. Table 7 shows the results of this estimation. Observations are at the startup level. The main variable of interest is $Z - score$, equal to the normalized parent fixed effects calculated using equations 1 and 2. In this regression, we control from the same individual-level characteristics (averaged at the startup level) as in Table 6, as well as one startup level control that counts the number of founders of the startup. Due to the relatively small number of observations, combined with the large number of countries (163) and industries (46) in our sample, we cannot saturate the regression with high-level fixed effects. Instead we control for startup characteristics at the country and industry levels using variables equal, respectively, to the country and industry fixed effects estimated using Equation 1.

Overall, the results confirm earlier findings but are a bit weaker economically and statistically: Firms created by employees exposed to high-fixed-effect parent firms are larger three years post-creation (column 1) and operate (i.e., have employees) in more countries (column 2). Although their startups are not more likely to close business at three-year horizon, they are more likely to face more extreme outcomes, i.e., to be acquired (as of 2025). Results are comparable when standard errors are bootstrapped (since we use a generated regressor) (Table 22).

If the phenomenon we document is driven by exposure to the entrepreneurial culture of spawners, it should be more pronounced the more intense the exposure is. We estimate exposure to the parent firm using two variables. First, we conjecture that exposure to the parent firm is stronger when an individual becomes an employee of the acquiring parent company, as opposed to remaining with their former employer. Information on employers in RevelioLabs allows us to distinguish these two career paths post-acquisition and to create a variable called *Integration*, equal to one when the employee is integrated to the acquirer post-acquisition and zero when the employee remains with the acquired firm.[6] Exposure to the entrepreneurial culture of prolific parents should also be more

[6]Examples of founders that are "Integrated" include (1) the founder of Rotera who was employed by McKinnis Consulting Services between 2010 and 2018, which was acquired in 2015 by Navigant. He subsequently moved to Navigant in 2016 before founding Venddy 2.4 years later; (2) the founder of Futureproof AI who was employed by Comet Global Consulting between 2015 and 2017, which was acquired by Merkle in 2016. He subsequently moved to Merkle in 2018 before founding Futureproof AI 1.4 years later.

intense the longer it lasts. To capture this, we create the variable *Stay*, equal to the number of years an alumni stays with their former employer (or with the acquiring parent company) post-acquisition. Since both variables measure the intensity of exposure to the parent firm, we expect their interaction with $Z - score$ to affect startup outcomes.

We examine this hypothesis in Tables 8 and 9, in which we replicate Table 7 adding an interaction between $Z - score$ and the two exposure intensity variables, *Integration* and *Stay*. Table 8 and Figure 5 show that integration of employees into acquiring prolific parents leads to larger startups that operate in more countries three years after foundation and to more patents. They also employ more engineers and receive more investments. Table 9 confirms these results using the length of the interaction with the parent firm as a measure of the intensity of exposure to its entrepreneurial culture. Results are comparable when standard errors are bootstrapped (since we use a generated regressor) (Table 23).

Next, we examine the mechanism through which exposure to prolific spawners affects the propensity of their alumni to become entrepreneurs and to create scalable firms. Several mechanisms can explain this. The first is a learning mechanism, whereby alumni replicate the business model or managerial practices they have observed at their former employer. If this mechanism was dominant, employees of high-fixed-effect firms would be more likely to create firms similar to those they worked for previously, that is, primarily in the same industry. We examine this possibility in Table 10, in which we repeat the baseline regression of Table 7. The dependent variables are dummy variables equal to one if the firm created by the alumni is in the same industry as the acquired firm (in column 1) or the parent firm (in column 2). The main explanatory variable of interest is $Z - score$, which captures the firm founder's exposure to a high- vs. low-fixed-effect parent. The results suggest that alumni exposed to prolific spawners are not more likely to create startups in the same industries as their parent firms.

The second possibility is that alumni of prolific spawners can create fast-growing startups thanks to a privileged access to the spawners' networks. This could translate into access to a large pool of talented employees working for prolific spawners that their alumni could tap into when they create their own companies. If this was the case, we would observe that alumni from prolific spawners tend to hire their employees from their former employers when they create their startups. Contrary to this conjecture, we observe in Table 11 that the employees are not more likely to be ex-employees of the acquiring firm just before joining the startup.

A second possible manifestation of this *network channel* can be easier access to financing networks of prolific spawners, which are themselves large companies that interact repeatedly with important actors of the financial system like banks and private investors. Prolific spawners also invest directly in new ventures through corporate VCs. Such corporate VCs could facilitate the expansion of newly-created startups. If they were at the origin of the creation of scalable startups, firm founders exposed to prolific spawners would be more likely to obtain funding from corporate VCs associated with their parent companies. Table 12 suggests that this is not the case.

A final mechanism that may explain the influence of prolific spawners on the entrepreneurial

outcomes of their alumni is the transmission of corporate culture from parent firms to the startups founded by their former employees. Some firms may cultivate organizational cultures that encourage ambition, growth orientation, or risk-taking. Exposure to such environments could shape employees' entrepreneurial aspirations and lead them to pursue more aggressive scaling strategies when founding their own firms. Directly measuring corporate culture at the firm level is challenging. However, using data from the World Values Survey, we can proxy for certain cultural traits at the country level and relate them to our earlier findings. In particular, the survey measures citizens' attitudes toward competition, often referred to as a *competition culture*. This notion reflects the extent to which individuals perceive competition as beneficial and motivating rather than harmful or socially undesirable. We conjecture that the influence of corporate culture on employees' preferences, such as their ambitions and entrepreneurial objectives, should be stronger when it diverges from prevailing local cultural norms. For instance, in countries where competition is viewed negatively, employment at firms that promote an ambitious and entrepreneurial corporate culture may have a stronger effect on employees. As a result, alumni of such firms may exhibit greater entrepreneurial ambition relative to local entrepreneurs than would be observed in countries where pro-competition attitudes are already widespread.

To test this conjecture and evaluate the possibility that corporate culture is a likely driver of our findings, we run a regression in which we explain the growth of startup companies three years post-creation. We use the same specification as in Table 7, notably the $Treatment$ variable, equal to one for parent firms with fixed effects larger than the median. We interact this variable with the $CompetitionIsHarmful$ variable taken from the World Value Survey, which measures whether citizens of a country see competition as more or less harmful.[7] The result in Table 13 confirms our conjecture: The employee count of startups three years post-creation is significantly larger for startups created by alumni of prolific spawners in countries in which competition is considered harmful.

6 Place-based policies

Next, we provide estimations of the extent to which parent firms in a given country contribute to employment in another country, for pairs of countries in our sample. To do so, we first calculate the *startup contribution abroad* of each parent firm. This variable is equal to the number of three-year forward jobs $(t+3)$ created by startups s founded in country C_s at time t by founders employed at time $t-1$ in country C_s by the parent firm P headquartered in country C_P such that $C_P \neq C_s$. Results displayed in the main text adjust for the number of co-founders. Employment generated abroad is positively associated with estimated fixed effects, as shown in Table 14. A one-standard deviation increase in effect is associated with a 60% increase in total three-year forward employment abroad, controlling for parent-country and parent-industry fixed effects. A back-of-the-envelope

[7] The World Values Survey measures attitudes toward competition using a question asking respondents to place their views on a 1–10 scale, where 1 means "competition is good" and 10 means "competition is harmful because it brings out the worst in people." We resort to WSV Wave 6 (2010–2014) and Wave 7 (2017–2022).

estimation yields the following result: 76.3% of total three-year forward non-endemic employment generated by startups in our sample is explained by spawners associated to above-median z-scores of spawner fixed effects, which account for about 0.30% of the 1,248,790 spawners generating at least one startup from 2021 to 2024 in RevelioLabs.

We next resort to the following thought experiment. For each country, we assess the share of employment that would be wiped out if the channel of non-endemic employment is shut down. In other words, we quantify the 'loss' in terms of three-year forward total employment generated in a given country C if we remove the employment generated by founders who were previously employed in C by a parent firm headquartered outside of C. A large non-endemic employment generation in a given country would imply that place-based policies tailored to attract entrepreneur-generating corporations from abroad can significantly affect job creation in the country. Table 14 and Figure 6 highlight the prevalence of non-endemic employment globally. Among countries in the top decile of total three-year forward employment, the median non-endemic share is 27%.

Next, we reiterate the same thought experiment, this time focusing only on non-endemic employment generated by U.S. firms. To do so, we calculate total employment generated in country C by startups founded by former employees of U.S. firms located in C. The evidence in Table 15 shows that, for some countries, such non-endemic employment represents a large fraction of total employment (e.g., 20% in Israel and India).

Next, we repeat the same exercise focusing on the share of top startups generated by U.S. firms, i.e., startups located in country C that are associated with a three-year forward employment above the top decile of the startup size distribution in country C. Table16 shows that U.S. parent firms also represent a large fraction of job creation in this category of startups, up to 20% in Israel.

Finally, we compute macro-level imbalances in terms of contributors and benefactors of this non-endemic employment channel in Table 17. We calculate for each country the difference between the total number of non-endemic jobs it creates abroad through its firms operating overseas and the total number of non-endemic jobs created in the country by foreign parent spawners. We aggregate three-year forward employment generated as such from 2010 to 2024. This is a measure of the net contribution to global employment growth by each country in our sample. In line with earlier results, the United States are the largest net contributors of employment in foreign countries. They *export* almost ten times as many jobs as the second largest contributor, i.e., the UK, net of *imported* jobs.

7 Conclusion

This paper shows that the origins of scalable startups are not randomly distributed across prior employers. Using global worker-level career histories matched to startup, financing, and patent data, we document that a relatively small set of organizations disproportionately produce founders whose ventures start larger, internationalize earlier, and pursue more acquisitive growth strategies. An acquisition-based exposure design further suggests that these patterns do not reflect selection alone:

when employees are reassigned into organizations with stronger founder-factory track records, the startups they later found are larger and more internationally dispersed. Taken together, the evidence implies that the supply of scalable entrepreneurial projects depends not only on founder ability and investor selection, but also on the organizational environments in which future founders work. An important agenda for future research is to identify more precisely what these environments transmit— awareness of scaling options, managerial know-how, or broader preferences for high stakes projects.

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8 Tables and Figures

8.1 Figures

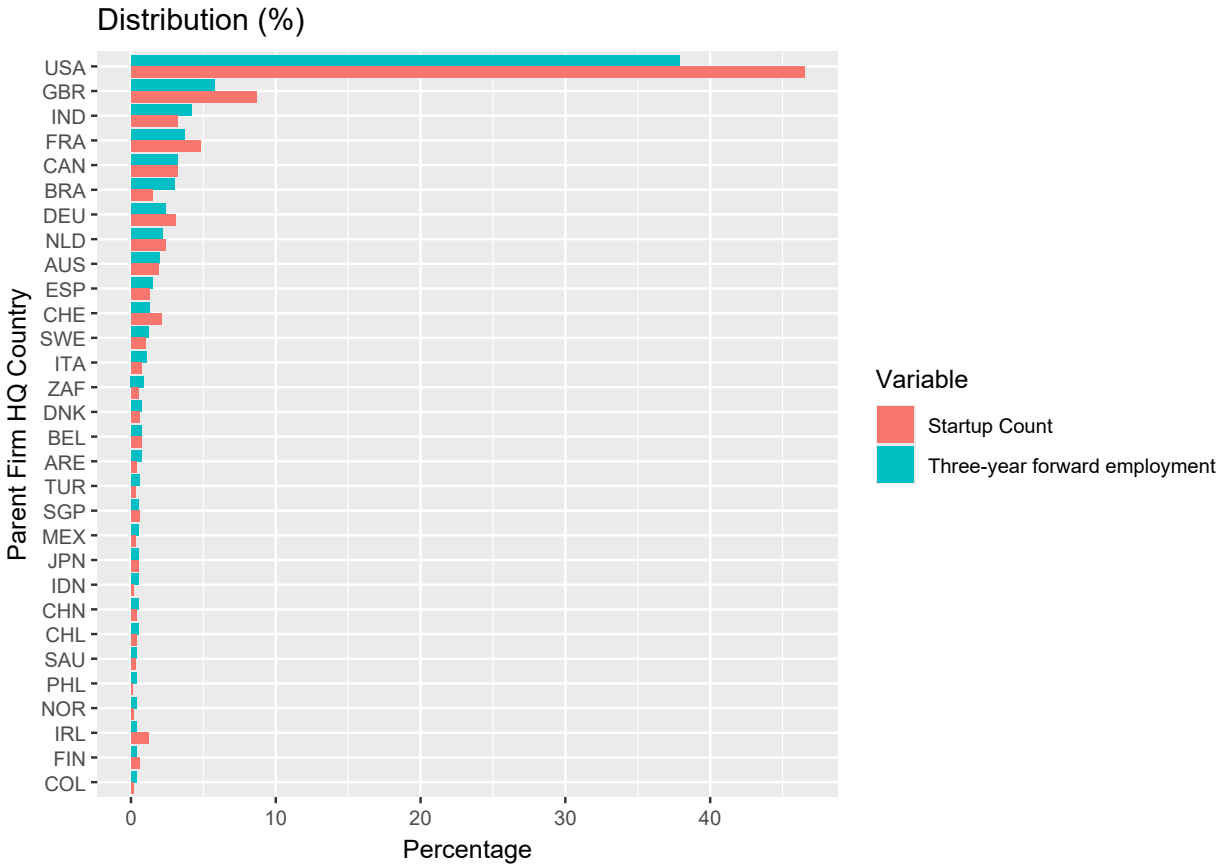


Figure 1.
Startup Count and Employment Creation by Country
This figure displays the percentage of startups and the cumulated employment they generate three years post-creation by country of their parent firm for the top 30 countries in our sample, ranked from largest to smallest contributor to three-year forward employment. (The ranking beyond the top 30 is in the Online Appendix.) We consider startups founded between 2010 and 2024 using RevelioLabs to identify new firms. For each startup we identify the parent firm, that is, the firm for which the founder of the startup worked last (in case of multiple founders, each parent firm is considered) and we assign the startup to its *country of origin* using the location of the parent's headquarter (in case of multiples startup founders and multiple parent firms located in multiple countries, we assign the startup to all the countries in which the startup's parents are located).

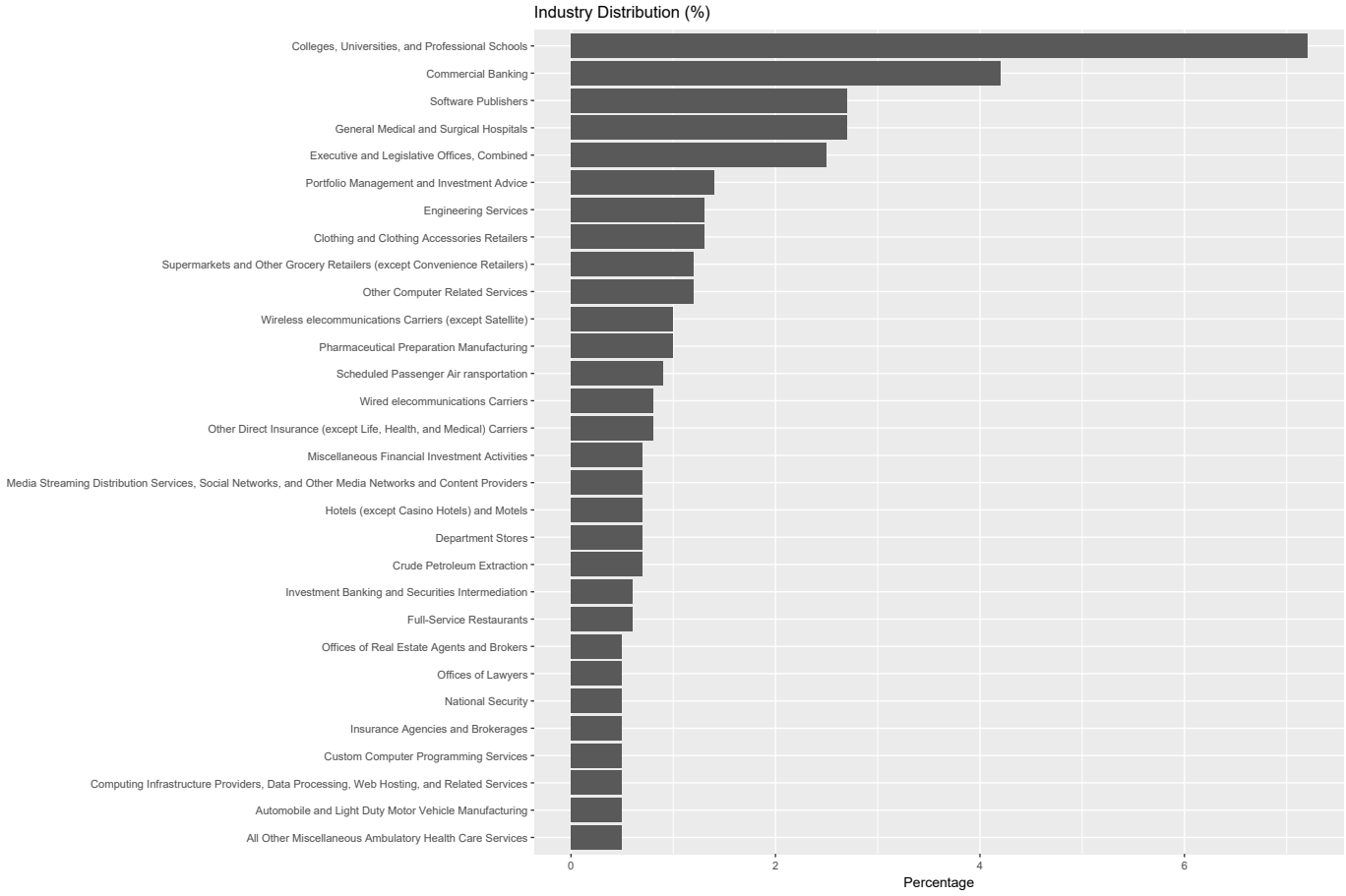


Figure 2.
Employment Creation by Industry
This figure displays the cumulated employment startups generate three years post-creation by industry of parent firms, ranked from largest to smallest contributor to three-year forward employment. We consider startups founded between 2010 and 2024 using RevelioLabs to identify new firms. For each startup we identify the parent firm, that is, the firm for which the founder of the startup worked last (in case of multiple founders, each parent firm is considered) and we assign the startup to its *industry of origin* using the industry of the parent firm (in case of multiples startup founders and multiple parent firms operating in multiple industries, we assign the startup to all the industries of the parents). We identify industry using the NAICS industry classification of the parent firm(s) provided by RevelioLabs.

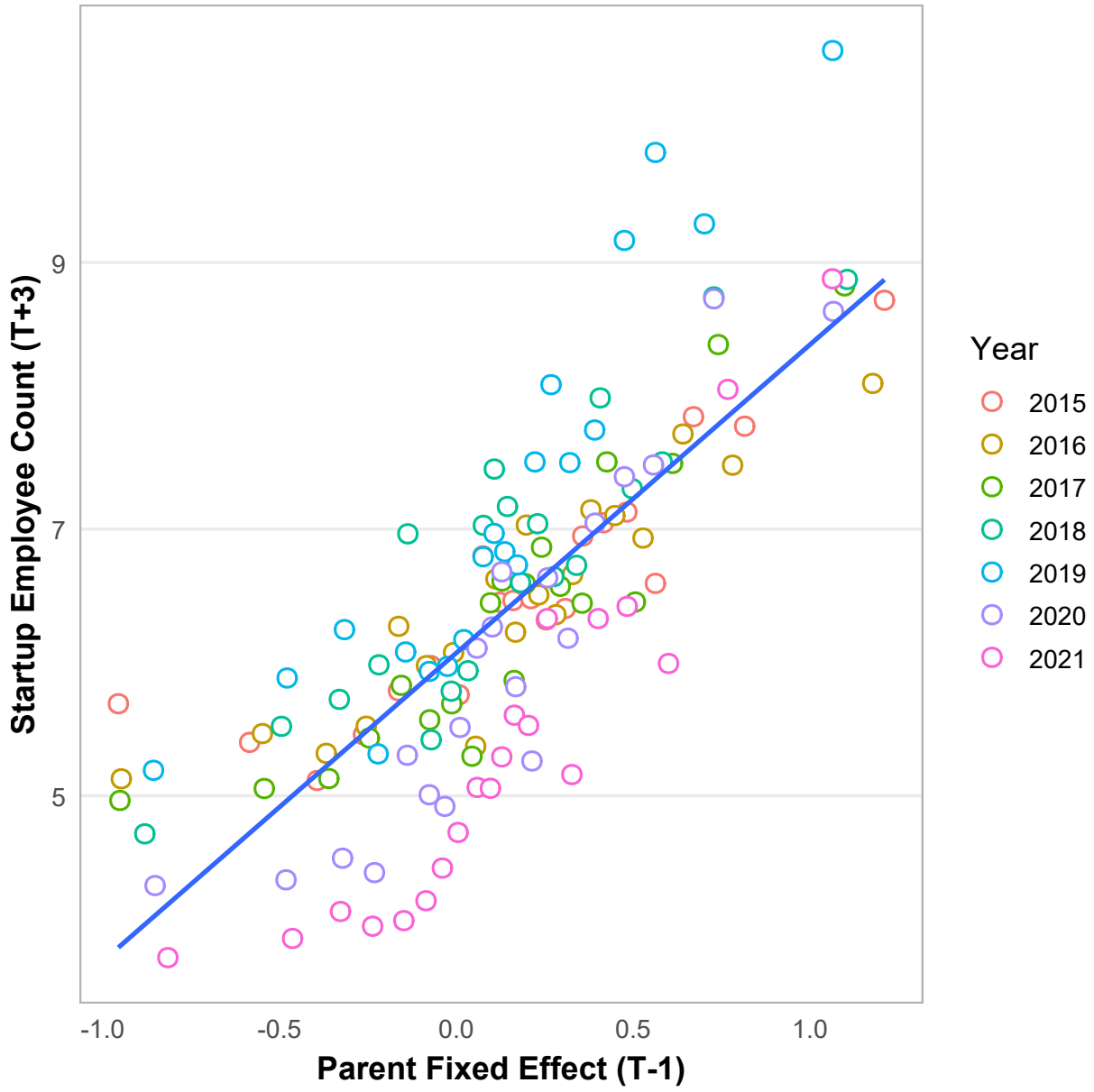


Figure 3.
Out-of-sample Persistence of Parent Fixed Effects
This figure shows that parent firm fixed effects predict startup scale *out-of-sample*. We implement a rolling-window estimation procedure using startups created between 2010 and 2021 (Revelio Labs). For each year T, we do 20 bins of parent firm fixed-effect, estimated using data prior to year T, and show on the y-axis the average employment at year $T + 3$ of startups created at year T from that bin. Each vintage T has its own binscatter plot, represented with a different color. The first estimation window uses data from 2010–2014 to predict outcomes for 2015 startups; the window is then expanded sequentially (2010–2015 predicting 2016, etc.) up to 2010–2020 predicting 2021. Because outcomes are measured three years after founding and the data end in 2024, 2021 is the last cohort for which outcomes can be observed. Parent firm fixed effects are obtained from a regression where the dependent variable is startup employment three years after founding, for all startups whose founders were last employed at the focal parent firm prior to founding. The specification includes controls for parent firm country and industry, startup year of incorporation, number of founders, and parent firm size (measured by employment), as described in Equations 1 and 2.

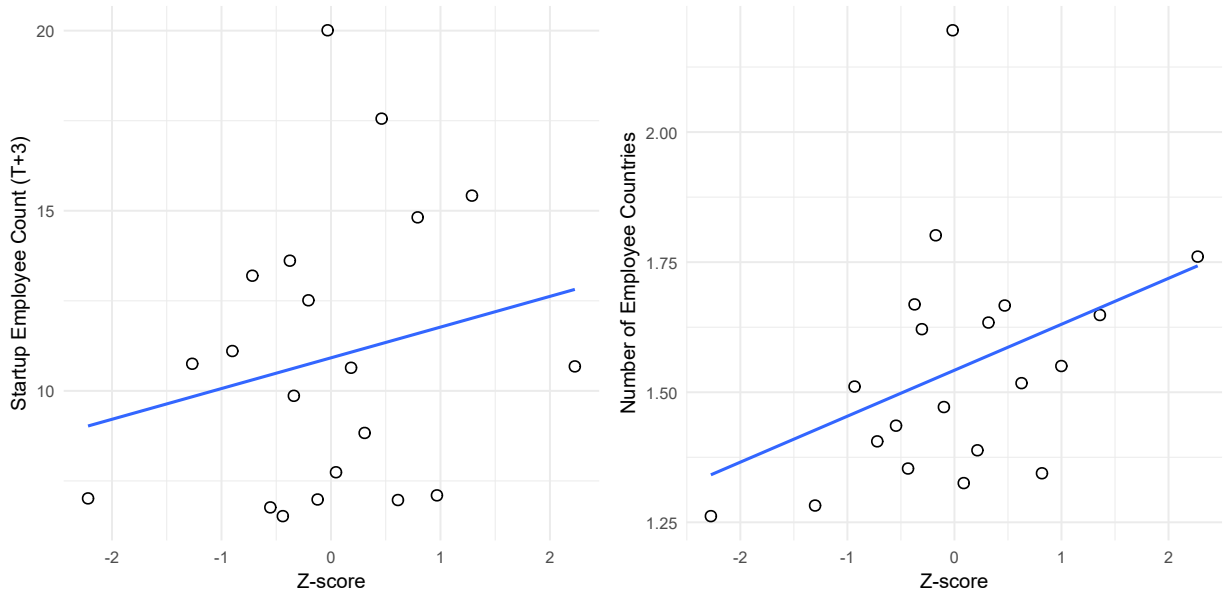


Figure 4.
Parent firm fixed effects and startup-level employee and country counts
This graph presents the link between parent firm fixed effects z-scores (x-axis) and three-year forward employment creation by startups created between 2010 and 2024 according to RevelioLabs in the left panel and the link between parent firm fixed effects z-scores (x-axis) and the number of countries in which startup employees are located three years post-creation in the right panel. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. We then breakdown the fixed effect z-scores into vigintiles and for each bin corresponding to a parent firm fixed effect z-score vigintile, we calculate the average three-year forward employment of startups generated by parent firms in that bin. Startup employee counts are conditional on three-year forward survival.

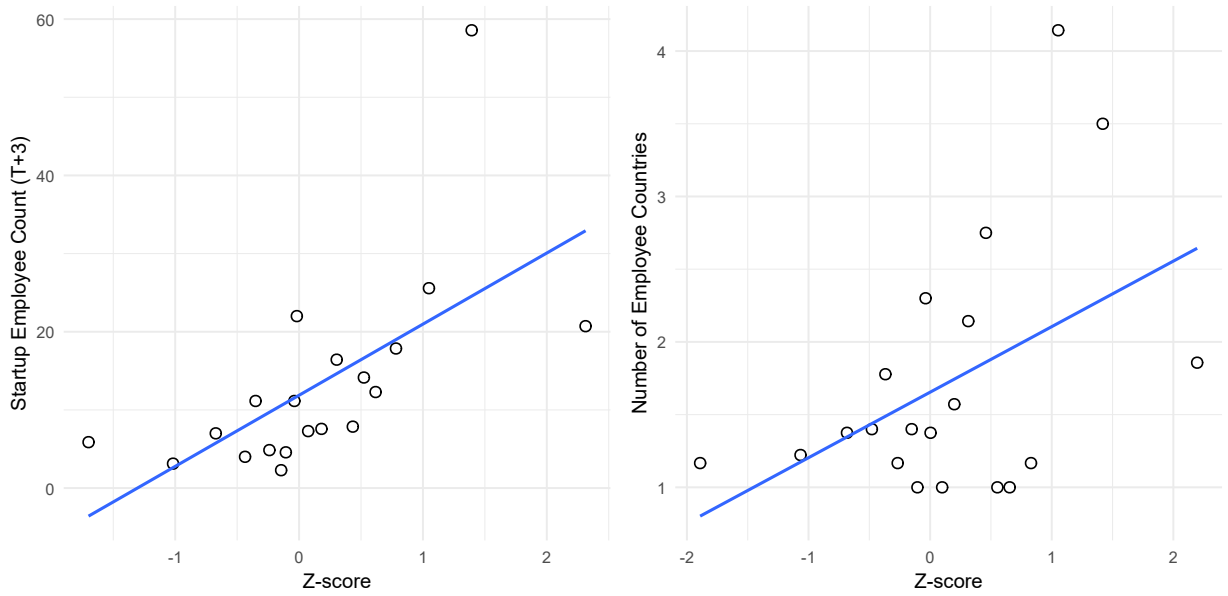


Figure 5.
Parent firm fixed effects and startup-level employee and country counts when founders are "Integrated" into acquiring firms
This graph presents the link between parent firm fixed effects (x-axis) and three-year forward employment creation by startups created between 2010 and 2024 according to RevelioLabs in the left panel and the link between parent firm fixed effects z-scores (x-axis) and the number of countries in which startup employees are located three years post-creation in the right panel. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. We then breakdown the fixed effect z-scores into vigintiles and for each bin corresponding to a parent firm fixed effect z-score vigintile, we calculate the average three-year forward employment of startups generated by parent firms in that bin. Startup employee counts are conditional on three-year forward survival. A founder is *Integrated* when she is integrated to the acquirer post-acquisition and zero otherwise.

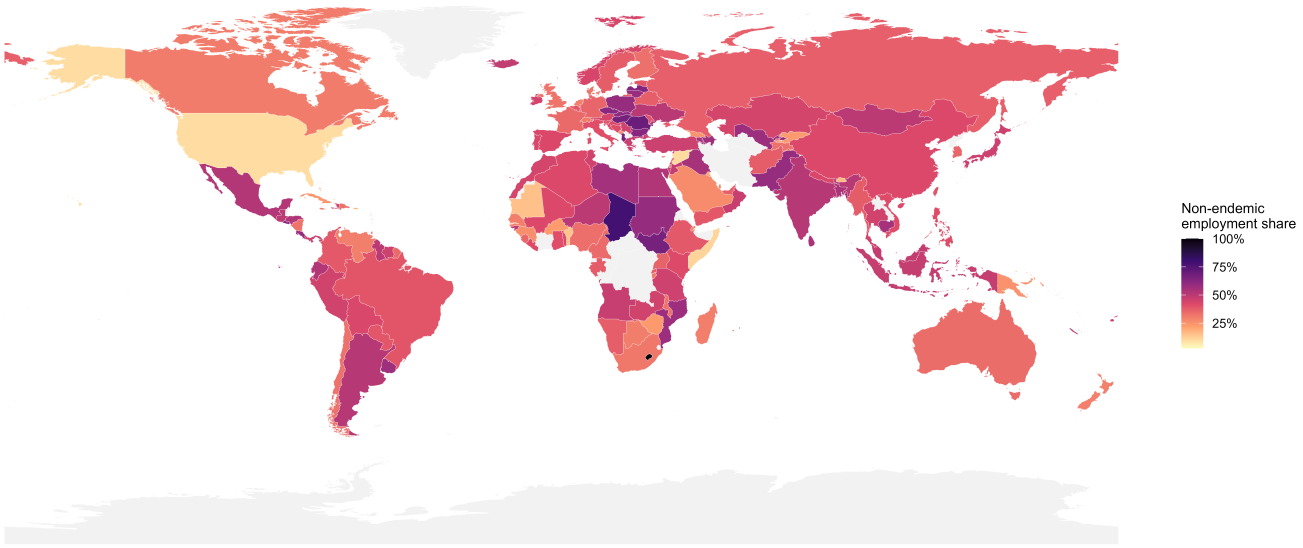


Figure 6.
Non-endemic Employment Share by Country
This Figure highlights the prevalence of *non-endemic* employment globally. To do so, we first calculate the *startup contribution abroad* of each parent firm. This variable is equal to the number of three-year forward jobs $(t+3)$ created by startups s founded in country C_s at time t by founders employed at time $t-1$ in country C_s by the parent firm P headquartered in country C_P such that $C_P \neq C_s$. For each country C_s, we then aggregate the number of such jobs and compute their share among total three-year forward employment generated. Results displayed adjust for the number of co-founders.

Variable	Mean	SD	P10	P90
Panel A: Founder and Startup Statistics				
Position number	6.76	4.09	3	11
Unique Past Employers	3.30	2.53	1	6
Seniority	5.74	1.05	5	7
Same country as Previous Employment	0.86	0.35	0	1
Unique Past Countries	1.40	0.74	1	2
Initial Startup Employee Count	2.67	3.50	1	5
Three-year forward Employee Count	5.87	11.43	1	13
Number of Founders	1.39	0.61	1	2
Panel B: Parent Firm Statistics				
Year Founded	1989.45	45.39	1935	2019
Is Public	0.09	0.29	0	0
Employee Count	9846.59	47227.89	2	10745

Table 1.
Founders, Startups and Parent Firms Average Characteristics
This table presents summary statistics for startups created between 2010 and 2024 according to RevelioLabs. Panel A presents summary statistics at the startup and founder levels. *Position number* is the number of positions occupied by the founder before the startup creation. *Unique past employers* is the number of firms in which the founder worked before the startup creation. *Seniority* is the founder's level in the hierarchy in their last pre-startup employment according to RevelioLabs, from 5 to 7. *Same country as previous employment* is equal to one if the startup is created in the same country as the founder's last employment and zero otherwise. *Unique past country* is the number of countries in which the founder worked before the startup creation. All variables are averaged across founders if the startup is created by multiple founders. *Initial startup employee count* is the number of employees at the creation of the startup. *Three-year forward startup employee count* is the number of employees three year after the creation of the startup, conditional on survival. Panel B presents summary statistics at the level of parent firms, in which founders worked before creating their startups. *Is public* is an indicator variable equal to one if the parent firm is publicly listed. *Employee count* is the number of employees in the parent firm three years after the creation of the startup.

Workplace$^{P}_{t-1}$	Startup Count^{s}	Share (%)	Total Employees$^{s}_{t+3}$	Share (%)
Microsoft Corp.	4256	0.22	17353	1.30
Google LLC	3997	0.20	19015	1.43
Deloitte LLP	3550	0.18	12440	0.93
Accenture Plc	3288	0.17	11552	0.87
International Business Machines Corp.	3234	0.16	11565	0.87
Upwork, Inc.	3012	0.15	5993	0.45
Amazon.com, Inc.	2988	0.15	8790	0.66
Ernst & Young Global Ltd.	2930	0.15	10341	0.78
Fiverr, Inc.	2081	0.11	3058	0.23
PricewaterhouseCoopers LLP	1963	0.10	7310	0.55
Apple, Inc.	1792	0.09	6191	0.46
YouTube LLC	1612	0.08	3157	0.24
Oracle Corp.	1609	0.08	5434	0.41
McKinsey & Co., Inc.	1568	0.08	10706	0.80
Citigroup, Inc.	1349	0.07	4698	0.35
HSBC Holdings Plc	1342	0.07	4260	0.32
Cisco Systems, Inc.	1256	0.06	5753	0.43
The Goldman Sachs Group, Inc.	1177	0.06	6595	0.50
Hewlett Packard Enterprise Development LP	1148	0.06	3611	0.27
Intel Corp.	1058	0.05	5512	0.41
UBS AG	1021	0.05	3661	0.27
SAP SE	1019	0.05	3980	0.30
The Boston Consulting Group, Inc.	1015	0.05	6255	0.47
Morgan Stanley	1015	0.05	3801	0.29
Dell, Inc.	1011	0.05	3140	0.24
Nokia Oyj	993	0.05	3701	0.28
Tata Consultancy Services Ltd.	977	0.05	3423	0.26
The United States Army	959	0.05	2242	0.17
Uber Technologies, Inc.	950	0.05	6035	0.45
Capgemini SE	949	0.05	3345	0.25

Table 2.
Top 30 parent firms by startup count
This table presents number of startups and three-year forward employment generated by the top 30 parent firms, as well as their shares in total startup and job creation. The ranking is based on the number of startups created by employees of parent firms between 2010 and 2024 according to RevelioLabs.

Dependent Variables:	log(1+Startup Count^P)				log(1+Employees$^{s,P}_{t+3}$)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
log(1+Employees$^P_{2010-2019}$)	0.3820***	0.8003***	0.8003***	0.8517***	0.4679***	0.9253***	0.9247***	0.9305***
	(0.0107)	(0.0038)	(0.0038)	(0.0076)	(0.0129)	(0.0064)	(0.0064)	(0.0092)
Founded Post-1990^P	-0.0872***	0.1700***	0.1713***	0.2656***	-0.1038***	0.3151***	0.3259***	0.5002***
	(0.0188)	(0.0055)	(0.0060)	(0.0066)	(0.0227)	(0.0146)	(0.0151)	(0.0292)
Average Inverse HHI$^P_{2010-2019}$	0.8079***	0.5520***	0.5527***	0.5712***	0.9889***	0.8576***	0.8639***	0.8436***
	(0.0944)	(0.0420)	(0.0411)	(0.0365)	(0.1135)	(0.0431)	(0.0411)	(0.0255)
Average STEM Employees$^P_{2010-2019}$	1.516***	0.7631***	0.7636***	0.7063***	1.935***	1.166***	1.169***	1.177***
	(0.0926)	(0.0636)	(0.0634)	(0.0987)	(0.1266)	(0.0745)	(0.0700)	(0.0943)
Average MBA Employees$^P_{2010-2019}$	5.088***	3.201***	3.197***	1.081***	6.246***	4.054***	4.022***	1.976***
	(0.2553)	(0.0534)	(0.0529)	(0.1018)	(0.3129)	(0.0434)	(0.0396)	(0.0758)
Average PhD Employees$^P_{2010-2019}$	1.816***	1.209***	1.219***	1.302***	2.416***	1.718***	1.800***	5.356***
	(0.1304)	(0.0617)	(0.0667)	(0.1743)	(0.1816)	(0.0712)	(0.0743)	(0.0862)
log(Acquisition Count^P)	0.8396***	0.2230***	0.2228***	0.1413***	1.046***	0.3020***	0.3006***	0.1699***
	(0.0339)	(0.0109)	(0.0107)	(0.0078)	(0.0414)	(0.0112)	(0.0109)	(0.0045)
Firm Scope Growth$^P_{2005-2010}$		0.0370***	0.0373***	0.0680***		0.0899***	0.0922***	0.1405***
		(0.0056)	(0.0054)	(0.0030)		(0.0055)	(0.0053)	(0.0034)
VC-Funded^P = 1			-0.0087	-0.0534***			-0.0728***	-0.1429***
			(0.0097)	(0.0095)			(0.0100)	(0.0129)
log(Average Market Cap$^P_{2010-2019}$)				0.1377***				0.1019***
				(0.0075)				(0.0039)
Fixed-effects								
Industry^P	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country^P	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Dependent variable mean	0.21676	2.5952	2.5952	3.6004	0.26807	3.1509	3.1509	4.3685
Observations	104,124	1,044	1,044	559	104,124	1,044	1,044	559
RMSE	0.47410	0.61279	0.61278	0.54446	0.60883	0.87631	0.87578	0.82896
R^2	0.68929	0.89231	0.89232	0.81038	0.67247	0.85292	0.85310	0.70048

Clustered (Country^P) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3.
Determinants of startup generation and startup growth
This table examines the parent-level determinants of spawning and startup growth. In the first four columns, we regress the number of startups created and, in columns 5 to 8, their three-year forward aggregate number of employees. We consider startups founded between 2010 and 2024 using RevelioLabs to identify new firms. For each startup we identify the parent firm, that is, the firm for which the founder of the startup worked last (in case of multiple founders, each parent firm is considered). Independent variables are defined in Appendix 9.2. All regressions also include industry and country fixed effects, industry being the industry of the parent firm according to RevelioLabs and country the country of location of its headquarters. Standard errors are clustered at the level of parent firm's headquarter countries.

Rank	Thirty Largest Parent Firms in the Top 10 percent	Thirty Largest Parent Firms in the Bottom 10 percent
1	3M Co.	The United States Postal Service
2	The Goldman Sachs Group, Inc.	Publix Super Markets, Inc.
3	Uber Technologies, Inc.	The Travelers Cos., Inc.
4	McKinsey & Co., Inc.	Eskom Holdings SOC Ltd.
5	QUALCOMM, Inc.	Chick-fil-A, Inc.
6	Bank of America Corp.	GameStop Corp.
7	Mindtree Ltd.	Wm Morrison Supermarkets Ltd.
8	The Boston Consulting Group, Inc.	Dick's Sporting Goods, Inc.
9	Macquarie Group Ltd.	PT Bank Mandiri (Persero) Tbk
10	FirstRand Ltd.	JBS SA
11	Stanford University	Securitas AB
12	The University of Texas at Austin	Sysco Corp.
13	Broadcom Inc.	Enterprise Holdings, Inc.
14	Mass General Brigham, Inc.	Meijer Cos. Ltd.
15	Barnes & Noble, Inc.	Next Plc
16	ING Groep NV	Outback Steakhouse of Florida LLC
17	Otis Worldwide Corp.	Cox Enterprises, Inc.
18	Teach For America, Inc.	Dairy Queen Canada
19	Harvard University	John Lewis Partnership Trust Ltd.
20	Bain & Co., Inc.	Olive Garden of Texas LLC
21	NVIDIA Corp.	Advance Auto Parts, Inc.
22	Hexaware Technologies Ltd.	Bath & Body Works, Inc.
23	Corning, Inc.	Menard, Inc.
24	Juniper Networks, Inc.	KeyCorp
25	ITC Ltd.	Dillard's, Inc.
26	Mizuho Financial Group, Inc.	Dollar Tree, Inc.
27	Massachusetts Institute of Technology	Assurant, Inc.
28	KPMG International Cooperative	Sonic Corp.
29	Bajaj Finserv Ltd.	Beaumont Health
30	ICON plc	Lojas Riachuelo SA

Table 4.
Largest Parent Firms in the Top and Bottom 10 Percent of Fixed Effects
This table presents the list of the 30 largest firms in the top 10% (left column) and in the bottom 10% (right column) of parent firm fixed effects. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2.

Dependent Variables:	Employees^s $(t=0)$	Countries^s	Has Acquisitions^s	Number of Acquisitions^s	Closed^s $(t+3)$	Is Acquired^s
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	Poisson	OLS	OLS	OLS	OLS
Variables						
FE^P	0.3459***	0.1818***	0.0023***	0.0027***	0.0153***	0.0060***
	(0.0093)	(0.0065)	(0.0005)	(0.0007)	(0.0025)	(0.0011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Country^P	Yes	Yes	Yes	Yes	Yes	Yes
Cohort^s-Industry^P	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Dependent variable mean	2.6365	1.3315	0.00309	0.00349	0.08362	0.00520
Observations	162,157	62,662	162,157	162,157	162,157	162,157
RMSE	4.3764	0.80247	0.05534	0.07543	0.27514	0.07113
R^2			0.00579	0.00501	0.01204	0.02295

Clustered (Country^P) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5.
Parent firm fixed effects and startup characteristics

This Table reports startup-level outcomes as a function of parent firm fixed effects. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. The regressions include country and *industry* × *cohort* fixed effects and controls for startup-level controls, as defined in Appendix 9.2. All regressions also include country and cohort-industry fixed effects, cohort being the year of creation of the startup, industry the industry of the parent firm according to RevelioLabs and country the country of location of its headquarters. Standard errors are clustered at the level of parent firm's headquarter countries.

Dependent Variable:	Is Founder$_{t+3}$
Model:	(1)
Variables	
Z-score	0.0006***
	(0.0002)
Experience$_t$	0.0011***
	(8.71×10^{-5})
Seniority$_t$	0.0046***
	(0.0001)
Fixed-effects	
Country^f	Yes
Industry^s x Acquisition Year	Yes
Fit statistics	
Dependent variable mean	0.01266
Observations	864,704
RMSE	0.11113
R^2	0.01229

Clustered (country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6.
Parent firm fixed effects and probability of entrepreneurship - Acquisition sample
This table reports regressions of indicator variables equal to one for employees of firms acquired by firms for which we calculate parent firm fixed effects if they create startups in the three years post-acquisition on parent firms' z-scores and controls. z-scores are normalized parent firm fixed effects. These fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. The regression includes country and *industry* × *year* fixed effects and controls for *Experience* and *Seniority* of the employee at the moment of the acquisition, as defined in Appendix 9.2. Standard errors are clustered at the country level.

Dependent Variables:	Employees^s $(t+3)$	Countries^s	Has Acquisitions^s	Number of Acquisitions^s	Closed^s $(t+3)$	Is Acquired^s
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	Poisson	OLS	OLS	OLS	OLS
Variables						
Z-score^s	0.0707***	0.0487***	0.0030**	0.0036**	0.0004	0.0042**
	(0.0063)	(0.0168)	(0.0014)	(0.0017)	(0.0052)	(0.0022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. mean	8.890	1.499	0.0030	0.0071	0.0745	0.0064
Fixed-effects						
Cohort^s	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,585	2,584	2,809	2,809	2,809	2,809
RMSE	35.398	2.3634	0.06974	0.08362	0.25825	0.10782
R^2			0.01918	0.02323	0.09116	0.05516

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7.
Parent firm fixed effects and startup characteristics - Acquisition sample

This Table reports startup-level outcomes as a function of parent firm z-scores calculated from parent firm fixed effects, for startups created by *alumni* of parent firms, i.e., individuals who worked for firms taken over by parent firms. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. The regressions include *cohort* fixed effects and controls for startup-level controls, as defined in Appendix 9.2. All regressions also include country and cohort-industry fixed effects, cohort being the year of creation of the startup, industry the industry of the parent firm according to RevelioLabs and country the country of location of its headquarters. Standard errors are clustered at the level of parent firm's headquarter countries.

Panel A. Startup Characteristics

Dependent Variables:	Employees^s $(t+3)$	Countries^s	Has Acquisitions^s	Number of Acquisitions^s	Closed^s $(t+3)$	Is Acquired^s
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	Poisson	OLS	OLS	OLS	OLS
Variables						
Z-score^s	0.0297***	0.0333	0.0015	0.0023	0.0043	0.0049*
	(0.0062)	(0.0223)	(0.0018)	(0.0020)	(0.0067)	(0.0027)
Integration^s	0.0037	0.0237	0.0061	0.0055	0.0408*	0.0105
	(0.0269)	(0.0791)	(0.0063)	(0.0072)	(0.0234)	(0.0096)
Z-score^s × Integration^s	0.3656***	0.1939**	0.0069	0.0045	-0.0484*	-0.0063
	(0.0181)	(0.0842)	(0.0075)	(0.0085)	(0.0279)	(0.0114)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. mean	8.890	1.499	0.0030	0.0071	0.0745	0.0064
Fixed-effects						
Cohort^s	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,585	2,479	2,686	2,686	2,687	2,686
RMSE	35.384	2.3965	0.06871	0.07794	0.25460	0.10404
R^2			0.01971	0.02660	0.08429	0.05120

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B. Investment and Patent Outcomes

Dependent Variables:	Receives Investments^s	Investments Received^s	Has Patent^s	Patent Count^s
Model:	(1)	(2)	(3)	(4)
Variables				
Z-score^s	-3.44×10^{-5}	-0.0014	-0.0004	0.0008
	(0.0029)	(0.0091)	(0.0033)	(0.0097)
Integration^s	0.0154	0.0245	0.0359***	0.0954***
	(0.0104)	(0.0320)	(0.0122)	(0.0362)
Z-score^s × Integration^s	0.0441***	0.1617***	-0.0004	0.0241
	(0.0128)	(0.0394)	(0.0135)	(0.0399)
Controls	Yes	Yes	Yes	Yes
Dep. Var. mean	0.0198	0.4951	0.0089	0.6195
Fixed-effects				
Cohort^s	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,398	3,398	2,017	2,017
RMSE	0.12945	0.39835	0.11261	0.33340
R^2	0.04948	0.04180	0.13452	0.12309

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8.
Post-acquisition integration to parent firms and startup outcomes

This Table reports regressions of startup-level outcomes as a function of parent firm z-scores calculated from parent firm fixed effects, for startups created by *alumni* of parent firms, i.e., individuals who worked for firms taken over by parent firms, interacted with *Integration*, an indicator variable equal to one for employees transferred to the parent company post-acquisition. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. All regressions include cohort fixed effects, cohort being the year of creation of the startup and controls for startup-level controls, as defined in Appendix 9.2

Panel A. Startup Characteristics

Dependent Variables:	Employees^s $(t+3)$	Countries^s	Has Acquisitions^s	Number of Acquisitions^s	Closed^s $(t+3)$	Is Acquired^s
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	Poisson	OLS	OLS	OLS	OLS
Variables						
Z-score^s	-0.1069***	0.0343	0.0013	0.0016	0.0157	0.0026
	(0.0135)	(0.0356)	(0.0029)	(0.0035)	(0.0109)	(0.0046)
Stay^s	-0.0216***	0.0011	0.0004	0.0006	-0.0020	0.0016
	(0.0036)	(0.0091)	(0.0008)	(0.0009)	(0.0028)	(0.0012)
Z-score^s × Stay^s	0.0545***	0.0044	0.0005	0.0006	-0.0046	0.0005
	(0.0036)	(0.0095)	(0.0008)	(0.0010)	(0.0029)	(0.0012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. mean	8.895	1.501	0.0030	0.0071	0.0746	0.0064
Fixed-effects						
Cohort^s	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,592	2,591	2,817	2,817	2,817	2,817
RMSE	35.352	2.3639	0.06964	0.08349	0.25832	0.10767
R^2			0.01939	0.02347	0.09204	0.05527

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B. Investment and Patent Outcomes

Dependent Variables:	Receives Investments^s	Investments Received^s	Has Patent^s	Patent Count^s
Model:	(1)	(2)	(3)	(4)
Variables				
Z-score^s	-0.0057	-0.0278*	0.0015	0.0014
	(0.0050)	(0.0156)	(0.0054)	(0.0158)
Stay^s	0.0013	0.0069*	-0.0001	0.0022
	(0.0013)	(0.0041)	(0.0015)	(0.0043)
Z-score^s × Stay^s	0.0025*	0.0114***	-0.0002	0.0011
	(0.0013)	(0.0041)	(0.0014)	(0.0042)
Controls	Yes	Yes	Yes	Yes
Dep. Var. mean	0.0199	0.4945	0.0089	0.6189
Fixed-effects				
Cohort^s	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,567	3,567	2,106	2,106
RMSE	0.13372	0.41821	0.11696	0.34153
R^2	0.04376	0.04195	0.11307	0.10276

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9.
Post-acquisition exposure duration and startup outcomes
This table reports regressions of startup-level outcomes as a function of parent firm z-scores calculated from parent firm fixed effects, for startups created by *alumni* of parent firms, i.e., individuals who worked for firms taken over by parent firms, interacted with *Stay*, an continuous variable equal to the number of years a founder stays with their former employer post-acquisition. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. All regressions include cohort fixed effects, cohort being the year of creation of the startup and controls for startup-level controls, as defined in Appendix 9.2

Dependent Variables:	Same Industry as Acquired Firm	Same Industry as Parent Firm
Model:	(1)	(2)
Variables		
Z-score	-0.0018	0.0165
	(0.0030)	(0.0102)
Controls	Yes	Yes
Fixed-effects		
Cohort^s	Yes	Yes
Fit statistics		
Dependent variable mean	0.01345	0.16003
Observations	1,561	1,331
RMSE	0.11446	0.36267
R^2	0.01296	0.02153

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10.
Imitation

This Table reports regressions of indicator variables equal to one if startups created by *alumni* of parent firms, i.e., individuals who worked for firms taken over by parent firms, are in the same industry as the acquired firm (column 1) or as the parent firm (column 2), as a function of parent firm z-scores obtained by normalizing parent firm fixed effects. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. All regressions include cohort fixed effects, cohort being the year of creation of the startup and controls for startup-level controls, as defined in Appendix 9.2.

Dependent Variable:	Startup Employee Is Sourced from Acquiring Firm
Model:	(1)
Variables	
Z-score	0.0019
	(0.0026)
log(Founder Count)	0.0133
	(0.0083)
log(Parent Firm Count)	-0.0286*
	(0.0154)
Fixed-effects	
Cohort^s-Industry^s	Yes
Fit statistics	
Dependent variable mean	0.01356
Observations	53,400
RMSE	0.11367
R^2	0.03394

Clustered (startup) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11.
Employee sourcing by startups post-acquisition
This table reports the regression, at the startup-employee level, of an indicator variable equal to one for employees of the startup hired from the parent firm that acquired the company for which startup founders worked pre-acquisition. The main independent variable is the parent firms' z-scores obtained by normalizing parent firm fixed effects. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. The regression includes cohort-industry fixed effects, cohort being the year of creation of the startup and industry its industry according to Crunchbase classification, startup-level controls, as defined in Appendix 9.2. Standard errors are clustered at the startup level.

Dependent Variable:	Corporate Venture from Parent
Model:	(1)
Variables	
Z-score^s	-0.0001
	(0.0004)
Controls	Yes
Fixed-effects	
Cohort^s	Yes
Fit statistics	
Dependent variable mean	0.00029
Observations	3,398
RMSE	0.01603
R^2	0.12624

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12.
Financing by startups post-acquisition

This table reports the regression, at the startup level, of an indicator variable equal to one for startups created by *alumni* of parent firms, i.e., individuals who worked for firms taken over by parent firms, and financed by the parent firm's corporate VC. The main independent variable is the parent firms' z-scores obtained by normalizing parent firm fixed effects. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. The regression includes cohort fixed effects, cohort being the year of creation of the startup and controls for startup-level controls, as defined in Appendix 9.2.

Dependent Variable:	Employees^s $(t+3)$
Model:	(1)
Variables	
Z-score	-0.5059***
	(0.0948)
Competition Is Harmful	-0.2876***
	(0.0235)
Z-score × Competition Is Harmful	0.1546***
	(0.0259)
Controls	Yes
Fixed-effects	
Year Founded	Yes
Fit statistics	
Dependent variable mean	11.090
Observations	2,524
RMSE	35.747

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13.
Competition

This table reports the regression, at the startup level, of the number of employees three years post-creation. We consider startups created by *alumni* of parent firms, i.e., individuals who worked for firms taken over by parent firms. The main independent variables are the parent firms' z-scores obtained by normalizing parent firm fixed effects, and its interaction with an indicator variable equal to one in countries in which competition is seen as harmful according to the World Value Survey. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. The regression includes cohort fixed effects, cohort being the year of creation of the startup and controls defined in Appendix 9.2.

Dependent Variables:	Employment Generated Abroad^P $(t+3)$	Employment Generated Abroad^s $(t+3)$
Model:	(1)	(2)
	OLS	Poisson
Variables		
Fixed Effect^P	0.5832***	0.3953**
	(0.1390)	(0.1728)
Fixed-effects		
Country^P	Yes	Yes
Industry^P	Yes	Yes
Fit statistics		
Dependent variable mean	2.3435	41.787
Observations	3,874	4,271
RMSE	1.4363	178.00
R^2	0.18970	

Clustered (Country^P) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 14.
Employment generated abroad
This table reports regressions of the number of jobs created abroad by startups three years after their creation as a function of parent firm z-scores calculated from parent firm fixed effects, for startups created by *alumni* of parent firms, i.e., individuals who worked for firms taken over by parent firms. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. All regressions include parent firm country and industry fixed effects. Standard errors are clustered at the level of parent firm countries.

Country	Non-endemic employment share	Share from US firms	US firm employment in general
Israel	0.38	0.20	0.10
India	0.38	0.20	0.08
Mexico	0.37	0.17	0.07
Singapore	0.35	0.12	0.11
Indonesia	0.31	0.12	0.02
Sweden	0.30	0.07	0.03
Spain	0.28	0.08	0.02
Brazil	0.28	0.09	0.03
France	0.27	0.08	0.03
Australia	0.27	0.11	0.04
United Kingdom	0.26	0.13	0.05
Turkey	0.26	0.09	0.02
Germany	0.25	0.09	0.04
Italy	0.25	0.08	0.02
Canada	0.25	0.13	0.06
Netherlands	0.23	0.09	0.02
Switzerland	0.22	0.09	0.05
United States	0.08	NA	0.28

Table 15.
Prevalence of *non-endemic* employment and US firm presence
This table shows the prevalence of *non-endemic* employment in countries in the top decile of total three-year forward employment generated between 2010 and 2024. We first calculate the *startup contribution abroad* of each parent firm, equal to the total number of jobs created abroad by startups founded by former employees of the parent firm three years after their creation. For each country, we then aggregate the number of such jobs and compute their share of the total employment generated by local startups three years after their creation, presented in Column 1. Columns 2 presents the same share of non-endemic employment, generated by U.S. firms only, and Column 3 reports the share of workers located in the country and employed by US-headquartered firms.

Country	US firm-driven top decile startup share
Israel	0.20
India	0.18
Mexico	0.16
Canada	0.13
United Kingdom	0.12
Australia	0.11
Germany	0.09
Brazil	0.08
Netherlands	0.08
Sweden	0.08
Italy	0.08
Switzerland	0.07
Spain	0.07
France	0.06

Table 16.
Prevalence of US firm-driven startups
This table presents the share of top decile startups, i.e., firms in the top decile of employees count at the country level three years post-creation, founded by former employees of US firms. We restrict the sample of countries to those located the top decile of total startup counts.

Country	Net Balance$_{t+3}$
United States	187936
United Kingdom	21446
Switzerland	9813
Ireland	7858
Japan	2289
Germany	2088
Netherlands	2056
Finland	1877
Luxembourg	1775
Bermuda	1222
India	-79944
Brazil	-20445
Spain	-13571
Indonesia	-9956
Canada	-9366
Australia	-8781
Mexico	-8766
Pakistan	-7975
Italy	-6983
Argentina	-6739

Table 17.
Macro-level imbalances
This table presents country-level imbalances between jobs created abroad by local firms and jobs created locally by foreign firms.

9 Appendix

9.1 Detailed sample construction methodology

We search for terms describing a founder in thirteen distinct languages that commonly appear in the raw_job_title column in RevelioLabs (English, Chinese, Spanish, Portuguese, Hindi, Arabic, Persian, Bengali, Russian, Japanese, German, French, Korean):

- founder
- founding
- fundador
- gründer
- fondateur
- 创始人
- 創設者
- 공동 창업
- 창립자
- 창업
- 起業家
- 起業
- основатель
- প্রতিষ্ঠাতা
- संस्थापक
- مؤسس

We then filter out founder support roles by removing any titles containing words such as: "Executive Assistant", "EA to", "Founder's Office", "efounder", "Chief of Staff to", "Assistant to", "Executive Advisor", "助理", "アシスタント", "助手", 'Founder Trustee', 'office of', 'intern', 'bras droit', 'bras-droit'.[8] We keep founding C-suite positions such as "Founding CEO" or "Founding CFO".[9] As a final cleaning step, we remove any title containing country terms to avoid capturing founders of country offices.[10] We keep firms that are founded after 2010 and which have an asso-

[8] r"founder's associate|founders associate|to the founding team|associate founder|founding member|" r"founding team|founding engineer|founding advocate|founding mentor|founder's office|founders office|" r"city co-founder|campus founder|campus co-founder|founder associate|future founders fellow|" r"chapter founder and president|founder advisor|founder fellow|innofounder|chapter co-founder|" r"founders associate intern|founders network member|founders foundation startup school member - cohort 2021|" r"founder office|branch founder|labs batch|advisor to founder|advisor to the founders|" r"founders' office|founder's office|founders' office"

[9] r"(?i)founding ceo|founding chief executive officer|founding cfo|founding chief financial officer|" r"founding coo|founding chief operating officer|founding cio|founding chief information officer|" r"founding cmo|founding chief marketing officer|founding cto|founding chief technology officer|" r"founding cso|founding chief security officer|founding chro|founding chief human resources officer|" r"founding cpo|founding chief product officer|founding cco|founding chief compliance officer|" r"founding cao|founding chief administrative officer|founding clo|founding chief legal officer|" r"founding cxo|founding chief experience officer|founding cro|founding chief risk officer"

[10] Korea, UK, USA, Czech, Hong Kong, Taiwan, Russia, Vietnam, India, China, France, Germany, Italy, Spain, Brazil, Canada, Mexico, Australia, New Zealand, Singapore, Malaysia, Indonesia, Thailand,

ciated LinkedIn url since the LinkedIn url serves as the linking variable to other datasets.[11] We restrict the sample of founders to satisfy the condition that a given founder belongs to the first ten employees that are associated to the founded startup. We remove any parent firm and founded firm which is noisy or unidentified, that is, startups containing generic and ambiguous workplaces such as "freelance", "stealth" or "independent". This data engineering process ensures that we remove generic denominations that are not associated to a unique startup entity such as "Stealth Co.", "Stealth Mode Startup Co.", "Freelance", "Self-Employed" or "Various Companies".[12]

Then, based on the founders and the founded firms extracted in the previous step, we resort to the following two distinct steps:

- First, we filter the entire RevelioLabs data to extract the entire employment history of each founder identified as described above. This allows us to study the corporate or institutional origins of those founders.
- Second, based on the firms that are founded by the founder identified as described above, we extract every users that have current or prior work experience at the respective startups. This ensures we can compute annual- and firm-level outcomes such as annual employee count or annual employee growth rate.

We identify the corporate or institutional origins of founders by looking at the founder's last employer $(t-1)$ before she founds her firm (t). We remove small employers by imposing an average spawner size of at least 1635 employees (99th percentile of the sample distribution over the sample period 2010 to 2019). Finally, we remove any internship positions and any positions lasting less than six months. This creates a founder-startup-$t-1$ employer-employee count-year panel.

Parent firm average employee count is winsorized at the 0.01 percent level.

Philippines, Netherlands, Belgium, Sweden, Norway, Denmark, Finland, Ireland, Scotland, Wales, England, Portugal, Greece, Switzerland, Austria, Turkey, Japan, South Africa, Egypt, Israel, Saudi Arabia, UAE, Argentina, Chile, Colombia, Peru, Poland, Hungary, Cuba, Jamaica, Morocco, Algeria, Nigeria, Kenya, Ethiopia, Ghana, Zimbabwe.

[11] The LinkedIn url is more stable than the domain. For example, the LinkedIn url of Oculus VR (founded in 2012) has been stable over time https://www.linkedin.com/company/oculus-vr/ whereas its domain name changed from http://www.oculus.com to https://www.meta.com/fr/en/quest/ following its acquisition by Meta (then Facebook) in 2014. Although in this case http://www.oculus.com redirects to https://www.meta.com/fr/en/quest/, it is an unreliable startup identifier.

[12] "freelance", "freelance-", "freelancing", "stealth", "independent", "indpendent", "self-empl", "selfemploy", "self–empl", "___", "various-", "various», "*various*1".

9.2 Variable Definitions

- Startup Count^{P}: At the parent firm level. This variable equals the total number of startups founded between 2010 and 2024 by individuals who were employed at P immediately prior to launching their startup.
- Employee$^{s,P}_{t+3}$: At the parent firm level. This variable equals the total number of three-year forward employees employed at startups s founded between 2010 and 2021 by individuals who were employed at P immediately prior to launching their startup.
- Employee$^{P}_{2010-2019}$: At the parent firm level. This variable is equal to the average annual number of employees working at firm P from 2010 to 2019. An unborn firm has NA employees.
- Founded Post-1990^{P}: At the parent firm level. This variable is a dummy equal to one if the firm P is founded after 1990 and zero otherwise.
- Average Inverse HHI$^{P}_{2010-2019}$: At the parent firm level. This variable is equal to the average annual inverse HHI associated to firm P from 2010 to 2019. Inverse HHI is computed as described in 9.2.1
- Average STEM Employees$^{P}_{2010-2019}$: At the parent firm level. This variable is equal to the average annual share of employees from P that are associated with a STEM-degree education from 2010 to 2019. A STEM-degree education is defined in 9.2.2
- Firm Scope Growth$^{P}2005-2010$: At the parent firm level. This variable is equal to the log growth of firm scope of operations from 2005 to 2010 as defined in Hoberg and Phillips (2025).
- Acquisition Count^{P}: At the parent firm level. This variable is equal to the number of acquisitions completed by firm P in the Tracxn acquisition database as of 2025.
- VC Funded^{P}: At the parent firm level. This variable is a dummy equal to one if the firm P has positive venture capital funding in Crunchbase as of 2023.
- Average Market Cap$^{P}_{2010-2019}$: At the parent firm level. This variable is equal to the average annual market cap of firm P in
- Industry^{P}: At the parent firm level. This is the NAICS associated to the parent firm in RevelioLabs.
- Country^{P}: At the parent firm level. This is the headquarter country associated to the parent firm retrieved from Compustat and Crunchbase.
- Experience$_{i,t}$: At the employee x job-position level. This RevelioLabs variable measures the sequential order of the position in the employee's career (e.g., it equals 6 if the current job is the employee's sixth position).
- Seniority$_{i,t}$: At the employee x job-position level. This RevelioLabs categorical variable measures the hierarchical order of the position within the employing organization. The lowest hierarchical category is 1 while the top category is 7.
- Cohort^{s}: At the startup s level. This variable is equal to the birth year of startup s.

9.2.1 Average Inverse HHI

This variable is at the company-level.

To measure a firm's international footprint based on the geographic distribution of its employees, we compute the inverse of the Herfindahl-Hirschman Index (HHI) on employment shares across countries. Let a firm f in year t employ workers across a set of countries C. Denote by $s_{fc}^{(t)}$ the share of the firm's workforce located in country $c \in C$ in year t. The HHI for firm f in year t is defined as:

$$\text{HHI}_f^{(t)} = \sum_{c \in C} \left(s_{fc}^{(t)} \right)^2$$

This index measures concentration in the sense that a value close to 1 indicates that the workforce is highly concentrated in a single country, while a lower value suggests a more distributed (international) footprint. To make interpretation more intuitive, we define the *inverse HHI* as:

$$\text{InverseHHI}_f^{(t)} = 1 - \text{HHI}_f^{(t)}$$

This transformation ensures that higher values correspond to a broader international presence.

9.2.2 STEM Degrees

This variable is at the company level and is obtained by computing the share of STEM-degree employees within a company.

Academic degrees are categorized in RevelioLabs into the following 17 unique categories:

Field
Accounting
Architecture
Biology
Business
Chemistry
Economics
Education
Engineering
Finance
Information Technology
Law
Marketing
Mathematics
Medicine
Nursing
Physics
Statistics

Table 18

Among those categories we keep the following seven categories to characterize STEM degrees: Biology, Chemistry, Engineering, Information Technology, Mathematics, Physics, Statistics. This ensures our definition is consistent with the degrees that qualify as STEM according to the DHS STEM Designated Degree Program List provided by the U.S. Department of Homeland Security (DHS).

9.3 Figures

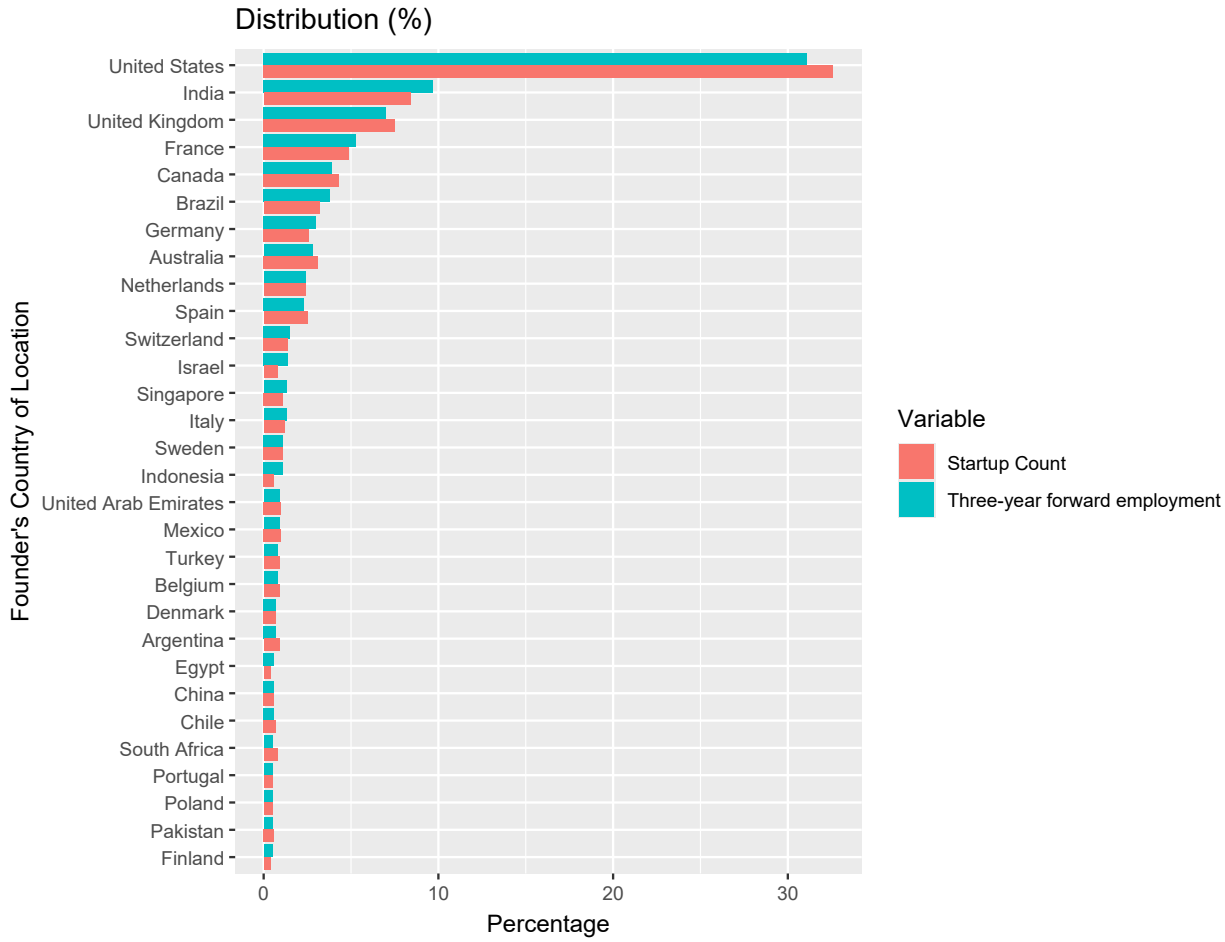


Figure 7.
Founder's Location Country
This figure displays the percentage of startups and the cumulated employment they generate three years post-creation by the startup founder's location when she founds her startup for the top 30 countries of location in our sample, ranked from largest to smallest contributor to three-year forward employment. (The ranking beyond the top 30 is in the Online Appendix.) We consider startups founded between 2010 and 2024 using RevelioLabs to identify new firms. For each startup we identify the parent firm, that is, the firm for which the founder of the startup worked last (in case of multiple founders, each parent firm is considered) and we assign the startup to its *country of origin* using the location of the parent's headquarter (in case of multiples startup founders and multiple parent firms located in multiple countries, we assign the startup to all the countries in which the startup's parents are located).

Dependent Variables:	Employees^s $(t=0)$	Countries^s	Has Acquisitions^s	Number of Acquisitions^s	Closed^s $(t+3)$	Is Acquired^s
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	Poisson	OLS	OLS	Poisson	OLS
Variables						
FE^P	0.3459***	0.1818***	0.0023***	0.0027***	0.1847***	0.0060***
	(0.0106)	(0.0070)	(0.0004)	(0.0005)	(0.0222)	(0.0005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Country^P	Yes	Yes	Yes	Yes	Yes	Yes
Cohort^s-Industry^P	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Dependent variable mean	2.6365	1.3315	0.00309	0.00349	0.08397	0.00520
Observations	162,157	62,662	162,157	162,157	161,482	162,157
RMSE	4.3764	0.80247	0.05534	0.07543	0.27573	0.07113
R^2			0.00579	0.00501		0.02295

Custom standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 19.
Parent firm fixed effects and startup characteristics (bootstrapped SE)
This Table reports startup-level outcomes as a function of parent firm fixed effects. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. The regressions include country and *industry* × *cohort* fixed effects and controls for startup-level controls, as defined in Appendix 9.2. All regressions also include country and cohort-industry fixed effects, cohort being the year of creation of the startup, industry the industry of the parent firm according to RevelioLabs and country the country of location of its headquarters. Standard errors are clustered at the level of parent firm's headquarter countries.

Dependent Variable:	Is Founder$_{t+5}$
Model:	(1)
Variables	
Z-score	0.0007**
	(0.0003)
Experience$_{t-1}$	0.0014***
	(0.0001)
Seniority$_{t-1}$	0.0055***
	(0.0002)
Fixed-effects	
country	Yes
Industry x Year	Yes
Fit statistics	
Dependent variable mean	0.01561
Observations	993,955
RMSE	0.12305
R^2	0.01437

Clustered (country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 20.
Probability of Entrepreneurship $(t+5)$

The unit of observation is an employee-year. The main variable of interest is $Z-score$, equal to the normalized parent fixed effects calculated using equations 1 and 2. We estimate the probability for alumni employees to found a startup in the three years following the acquisition of the firm they work for depending on the z-score of their parent firm. We control for employee-level characteristics at the time of acquisition: *seniority*, taken from RevelioLabs and taking values from 1 (low) to 7 (high), proxies for the individual's position in the hierarchy. *experience* is the number of positions the individual has occupied since they appear in RevelioLabs. We also include $country \times year$, $industry \times year$ and $country \times industry$ fixed effects to control for country and industry unobservables. The table shows that alumni acquired by prolific spawners are more likely to become entrepreneurs, by about 0.07% on average.

Dependent Variable:	Is Founder$_{t+3}$
Model:	(1)
Variables	
Z-score	0.0006***
	(0.0002)
Controls	Yes
Fixed-effects	
country	Yes
Industry x Year	Yes
Fit statistics	
Dependent variable mean	0.01266
Observations	864,704
RMSE	0.11113
R^2	0.01229

Custom standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 21.
Probability of Entrepreneurship (bootstrapped SE)

The unit of observation is an employee-year. The main variable of interest is $Z - score$, equal to the normalized parent fixed effects calculated using equations 1 and 2. We estimate the probability for alumni employees to found a startup in the three years following the acquisition of the firm they work for depending on the z-score of their parent firm. We control for employee-level characteristics at the time of acquisition: *seniority*, taken from RevelioLabs and taking values from 1 (low) to 7 (high), proxies for the individual's position in the hierarchy. *experience* is the number of positions the individual has occupied since they appear in RevelioLabs. We also include $country \times year$, $industry \times year$ and $country \times industry$ fixed effects to control for country and industry unobservables. The table shows that alumni acquired by prolific spawners are more likely to become entrepreneurs, by about 0.07% on average.

Dependent Variables:	Employees^s $(t+3)$	Countries^s	Has Acquisitions^s	Number of Acquisitions^s	Closed^s $(t+3)$	Is Acquired^s
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	Poisson	OLS	OLS	Poisson	OLS
Variables						
Z-score^s	0.0862	0.0556***	0.0030**	0.0036***	0.0210	0.0042**
	(0.0572)	(0.0179)	(0.0012)	(0.0013)	(0.0581)	(0.0020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. mean	8.890	1.499	0.0030	0.0071	0.0745	0.0064
Fixed-effects						
Cohort^s	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,811	2,583	2,808	2,808	2,778	2,808
RMSE	35.080	2.3088	0.06975	0.08363	0.24513	0.10784
R^2			0.01918	0.02323		0.05516

Custom standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 22.
Parent firm fixed effects and startup characteristics - Acquisition sample (bootstrapped SE)

This Table reports startup-level outcomes as a function of parent firm z-scores calculated from parent firm fixed effects, for startups created by *alumni* of parent firms, i.e., individuals who worked for firms taken over by parent firms. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. The regressions include *cohort* fixed effects and controls for startup-level controls, as defined in Appendix 9.2. All regressions also include country and cohort-industry fixed effects, cohort being the year of creation of the startup, industry the industry of the parent firm according to RevelioLabs and country the country of location of its headquarters. Standard errors are clustered at the level of parent firm's headquarter countries.

Panel A. Startup Characteristics

Dependent Variables:	Employees^s $(t+3)$	Countries^s	Has Acquisitions^s	Number of Acquisitions^s	Closed^s $(t+3)$	Is Acquired^s
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	Poisson	OLS	OLS	Poisson	OLS
Variables						
Z-score^s	0.0127	0.0427*	0.0015	0.0023	0.0641	0.0049*
	(0.0724)	(0.0229)	(0.0016)	(0.0015)	(0.0803)	(0.0025)
Integration^s	-0.2657*	0.0328	0.0061	0.0055	0.4397	0.0105
	(0.1570)	(0.0855)	(0.0074)	(0.0076)	(0.3088)	(0.0121)
Z-score^s × Integration^s	0.6205***	0.1824*	0.0069	0.0045	-0.6132	-0.0063
	(0.1709)	(0.1049)	(0.0078)	(0.0056)	(0.4916)	(0.0075)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. mean	8.890	1.499	0.1456	0.0030	0.0071	0.0064
0.0198	0.4951	0.0089	0.6195			
Fixed-effects						
Cohort^s	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,687	2,478	2,685	2,685	2,656	2,685
RMSE	35.267	2.3402	0.06873	0.07795	0.24242	0.10406
R^2			0.01971	0.02660		0.05120

Custom standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B. Investment and Patent Outcomes

Dependent Variables:	Receives Investments^s	Investments Received^s	Has Patent^s	Patent Count^s
Model:	(1)	(2)	(3)	(4)
Variables				
Z-score^s	0.0133***	0.0224	-0.0004	0.0457
	(0.0042)	(0.1437)	(0.0021)	(0.0734)
Integration^s	0.0258	0.8854	0.0359*	1.026
	(0.0161)	(1.229)	(0.0212)	(0.6498)
Z-score^s × Integration^s	0.0455*	8.303	-0.0004	0.2686
	(0.0262)	(6.690)	(0.0231)	(0.5524)
Controls	Yes	Yes	Yes	Yes
Dep. Var. mean	0.0198	0.4951	0.0089	0.6195
Fixed-effects				
Cohort^s	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,398	3,398	2,017	2,017
RMSE	0.17698	18.536	0.11261	4.2407
R^2	0.05790	0.02581	0.13452	0.08843

Custom standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 23.
Post-acquisition integration to parent firms and startup outcomes (bootstrapped SE)
This Table reports regressions of startup-level outcomes as a function of parent firm z-scores calculated from parent firm fixed effects, for startups created by *alumni* of parent firms, i.e., individuals who worked for firms taken over by parent firms, interacted with *Integration*, an indicator variable equal to one for employees transferred to the parent company post-acquisition. Parent firm fixed effects are the residuals from a regression in which the dependent variable is the number of employees three years post-creation of all startups originating from the focal parent firm (i.e., for which the founder worked at the parent firm last before creating the startup) between 2010 and 2024 and the main independent variable is the parent firm fixed effect, controlling for parent firm's country and industry fixed effects, year of incorporation and number of founders, as well as the size of the parent firm in number of employees, as described in equations 1 and 2. All regressions include cohort fixed effects, cohort being the year of creation of the startup and controls for startup-level controls, as defined in Appendix 9.2